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**Action Regulation in Energy-Efficient Driving: Analysing the Effects on  
Perception, Comprehension, Judgements,  
and Behaviour**

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## Abstract

Battery electric vehicles (BEVs) offer substantial potential for reducing emissions but introduce cognitive and behavioural challenges for energy-efficient driving. In contrast to internal combustion engine vehicles (ICEVs), energy flow in BEVs is less tangible, and relevant consumption patterns are more complex to perceive, predict, and interpret. Current ecodriving research often lacks cognitive grounding, a focus on the specific challenges in BEVs, and a profound analysis beyond performance measures.

This dissertation addresses the need for user-centred, cognitively aligned feedback by examining how different feedback approaches affect drivers' perception, judgements, behaviour, knowledge, and perceived support of action regulation and the mental model of ecodriving. The theoretical foundation integrates adaptive control and action regulation models, cognitive information processing, and the role of mental models and perceived capability in goal-directed behaviour. It posits that energy-efficient driving with BEVs requires continuous situational adaptation and knowledge-based reasoning.

Four empirical studies were conducted using experimental designs combined with qualitative and quantitative methods across diverse settings, including an online experiment, driving simulations, and real-world driving. Each study assessed both subjective and objective indicators of action regulation and knowledge.

**Study 1** ( $N = 55$ , online experiment) laid the conceptual foundation by exploring how drivers interpret typical consumption feedback derived from simplified acceleration dynamics. Rooted in bounded rationality, results revealed a systematic overestimation of energy use, particularly for high and brief maximum consumption values. There was no significant correlation between the correct energy efficiency ranking and the ranking derived from participants' estimations. The study also identified interindividual differences in heuristic information processing, showing that both stimulus properties and cognitive predispositions shape perception.

**Study 2** ( $N = 63$ , driving simulator study) focused on knowledge gaps and their behavioural implications. It contrasted three feedback approaches: a baseline without support, a consumption trace display, and a recommendation system indicating optimal speed. Drivers frequently relied on incomplete or inaccurate conceptions of energy efficiency. While those using the recommendation system felt less uncertain, this confidence did not translate into better performance or more accurate knowledge. However, their tendency to verbalise more vehicle- and environment-related information suggests a more active reasoning process regarding energy-efficient driving.

**Study 3** ( $N = 50$ , field study) built on these findings and introduced a comprehension-based approach with pre-drive tip lists. When behavioural strategies were paired with technical reasoning, drivers reported higher perceived knowledge, stronger support for action regulation and the mental model, and better driving performance. This highlights the potential of explanation-based feedback to improve effectiveness, knowledge, and user experience.

**Study 4** ( $N = 112$ , driving simulator study) extended this approach into real-time driving by integrating elaborated auditory ecodriving tips into a recommendation system. This combined approach significantly improved driving performance and strengthened perceived mental model support, although cognitive load, information acquisition, and subjective information processing awareness were negatively influenced.

The dissertation offers novel instruments and methods to evaluate ecodriving feedback. Key contributions include a new experimental paradigm for assessing dynamic magnitude perception, and two new constructs: perceived support of action regulation and perceived support of the mental model, enabling a finer-grained evaluation of action regulation quality beyond conventional usability or satisfaction metrics. Furthermore, existing items for measuring perceived ecodriving knowledge were revised based on theoretical considerations. Finally, an AI-assisted method was employed to systematically analyse verbalised driving strategies and their technical explanations, demonstrating scalable content analysis.

Theoretically, the dissertation integrates psychological frameworks with an emphasis on mental models and information processing, provides a systematic literature review, and links various feedback approaches to cognitive processing and behavioural regulation. Moreover, it extends established cognitive biases by identifying a novel bias specific to dynamic data visualisation. Empirically, it demonstrates that comprehension-oriented feedback can improve energy-efficient behaviour, deepen understanding, and enhance perceived support, especially when it explains behavioural strategies and clarifies causal relationships. The practical implications are synthesised into design guidelines for future feedback systems in BEVs and beyond.

The innovations in this dissertation extend beyond the context of BEVs. Action regulation in complex and dynamic systems—such as aviation, industrial control, or AI-assisted decision-making, especially in light of the growing role of generative, speech-based AI—can benefit from these findings. When users must form accurate mental models or interpret raw data in real-time, feedback should explain mechanisms and facilitate information analysis rather than merely presenting outcomes. This dissertation lays the groundwork for future research on cognitively aligned feedback systems that foster effective action regulation, adequate mental models, and user experience.

## Zusammenfassung

Batterieelektrische Fahrzeuge (BEVs) bieten ein erhebliches Potenzial zur Emissionsreduktion, stellen jedoch auch kognitive und verhaltensbezogene Herausforderungen für Fahrende dar. Im Vergleich zu Fahrzeugen mit Verbrennungsmotor (ICEVs) ist der Energiefluss in BEVs weniger greifbar, und relevante Verbrauchsmuster sind schwieriger wahrzunehmen, vorherzusagen und zu interpretieren. Die aktuelle Forschung zur Unterstützung energieeffizienten Fahrens weist häufig eine unzureichend fundierte Berücksichtigung kognitiver Aspekte auf, berücksichtigt die speziellen Herausforderungen von BEVs nicht ausreichend und bietet selten eine tiefgehende Analyse jenseits von Leistungsmaßen.

Diese Dissertation greift den Bedarf an nutzerzentrierter, kognitiv anschlussfähiger Systemunterstützung in BEVs auf, indem sie untersucht, wie unterschiedliche Feedbackansätze die Wahrnehmung, Urteile, das Verhalten, Wissen sowie die wahrgenommene Unterstützung der Handlungsregulation und des mentalen Modells von Fahrenden beeinflussen. Die theoretische Grundlage integriert Modelle adaptiver Handlungskontrolle bzw. -regulation, kognitiver Informationsverarbeitung sowie die Rolle mentaler Modelle und wahrgenommener Kompetenz im zielgerichteten Verhalten. Es wird postuliert, dass energieeffizientes Fahren in BEVs eine kontinuierliche situative Anpassung und wissensbasiertes Schlussfolgern erfordert.

Es wurden vier empirische Studien mit experimentellen Designs sowie qualitativen und quantitativen Methoden durchgeführt. Die Settings reichten von einem Online-Experiment, Fahrsimulationsstudien bis hin zu einer Feldstudie. Jede Studie erfasste sowohl subjektive als auch objektive Indikatoren der Handlungsregulation und des Wissens.

**Studie 1** ( $N = 55$ , Onlineexperiment) legte das konzeptionelle Fundament, indem sie untersuchte, wie Fahrende typisches Verbrauchsfeedback interpretieren, das auf vereinfachten Beschleunigungsdynamiken basiert. Auf Grundlage der Theorie begrenzter Rationalität zeigte sich eine systematische Überschätzung des Energieverbrauchs, insbesondere bei kurzen und hohen Maximalwerten. Zwischen der korrekten Energieeffizienz-Rangfolge und der von den Schätzungen abgeleiteten Rangfolge bestand keine signifikante Korrelation. Zudem wurden interindividuelle Unterschiede in der heuristischen Informationsverarbeitung deutlich: Sowohl Reizeigenschaften als auch kognitive Dispositionen beeinflussen die Wahrnehmung.

**Studie 2** ( $N = 63$ , Fahrsimulatorstudie) richtete den Fokus auf Wissenslücken und deren Auswirkungen auf das Verhalten. Es wurden drei Feedbackansätze untersucht: eine Basisbedingung ohne Systemunterstützung, eine Anzeige des Verbrauchs über die Zeit und ein Empfehlungssystem zur Anzeige optimaler Geschwindigkeit. Viele Fahrende verfügten über inkonsistente oder unvollständige Vorstellungen von energieeffizienten Fahrstrategien. Obwohl das Empfehlungssystem Unsicherheiten verringerte, steigerte es weder die Leistung noch das

Wissen signifikant. Die verstärkte Verbalisierung von fahrzeug- und umgebungsbezogenen Informationen deutet jedoch auf einen stärkeren Prozess aktiven Schlussfolgerns hin.

**Studie 3** ( $N = 50$ , Feldstudie) baute auf den Vorarbeiten auf und führte einen verständnisorientierten Ansatz ein, bei dem vor der Fahrt Tipplisten zur Verfügung gestellt wurden. Wurden Verhaltensstrategien mit technischer Begründung kombiniert, zeigten Fahrende einen höheren Wissenszuwachs und berichteten eine stärkere Unterstützung der Handlungsregulation und des mentalen Modells. Außerdem zeigten sie eine bessere Fahrleistung. Das unterstreicht das Potenzial erklärungsbasierter Feedbacks zur Verbesserung von Effektivität, Wissen und Nutzererleben.

**Studie 4** ( $N = 112$ , Fahrsimulatorstudie) übertrug den erklärungsorientierten Ansatz in den Echtzeitkontext, indem erlaborierte akustische Tipps in ein Empfehlungssystem integriert wurden. Die Kombination verbesserte signifikant die Fahrleistung und stärkte die wahrgenommene Unterstützung des mentalen Modells. Gleichzeitig kam es zu höherer kognitiver Belastung sowie zu einer negativen Beeinflussung der Informationsaufnahme und des subjektiven Bewusstseins für die Informationsverarbeitung.

Die Dissertation bietet neue Instrumente und Methoden zur Bewertung von Ecodriving-Feedback. Zu den wichtigsten Beiträgen zählen ein neues experimentelles Paradigma zur Beurteilung der Wahrnehmung dynamischer Größen sowie zwei neue Konstrukte: die wahrgenommene Unterstützung der Handlungsregulation und die wahrgenommene Unterstützung des mentalen Modells. Diese ermöglichen eine differenziertere Evaluation der subjektiven Qualität der Handlungsregulation, die über herkömmliche Usability- oder Zufriedenheitsmetriken hinausgeht. Zudem wurden bestehende Items zur Erfassung des wahrgenommenen Ecodriving-Wissens theoriegeleitet überarbeitet. Schließlich wurde eine KI-gestützte Methode eingesetzt, um verbalisierte Fahrstrategien und deren technische Erklärungen systematisch zu analysieren, was eine skalierbare Inhaltsanalyse ermöglicht.

Theoretisch integriert die Dissertation psychologische Modelle mit Schwerpunkt auf mentalen Modellen und Informationsverarbeitung, liefert eine systematische Literaturübersicht und verknüpft verschiedene Feedbackansätze mit kognitiver Verarbeitung und Verhaltensregulation. Darüber hinaus erweitert sie etablierte kognitive Verzerrungen durch die Identifikation eines neuartigen Bias, der speziell bei der Visualisierung dynamischer Daten auftritt. Empirisch zeigt die Arbeit, dass verständnisorientiertes Feedback energieeffizientes Verhalten fördert, das Verständnis vertieft und die wahrgenommene Unterstützung erhöhen kann – insbesondere wenn es Verhaltensstrategien erklärt und kausale Zusammenhänge zwischen Ursache und Wirkung verdeutlicht. Die praktischen Implikationen werden in Form von Gestaltungsrichtlinien für zukünftige Feedbacksysteme in BEVs und darüber hinaus zusammengefasst.

Die Innovationen der Dissertation gehen über den Kontext von BEVs hinaus. Die Handlungsregulation in komplexen und dynamischen Systemen wie Luftfahrt, industrieller Steuerung oder KI-gestützten Entscheidungsprozessen – insbesondere vor dem Hintergrund der wachsenden Bedeutung generativer, sprachbasierter KI – kann von den Ergebnissen profitieren. Wenn Nutzer genaue mentale Modelle bilden oder Rohdaten in Echtzeit interpretieren müssen, sollte Feedback Mechanismen erklären und die Informationsanalyse erleichtern, anstatt nur Ergebnisse zu präsentieren. Diese Dissertation legt die Grundlage für zukünftige Forschung zu kognitiv abgestimmten Feedbacksystemen, die eine effektive Handlungsregulation, adäquate mentale Modelle und ein positives Nutzererlebnis fördern.

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## List of Abbreviations

ART	Action Regulation Theory
BEV	Battery electric vehicle
CZM	Comfort-Zone Model
EV	Electric vehicle
GALA	General Automation Level Allocation
GHG	Greenhouse gas
HEV	Hybrid electric vehicle
HMI	Human-machine interface
ICEV	Internal combustion engine vehicle
PCT	Perceptual Control Theory
RO	Research objective
TCI	Task–Capability Interface

## 1. Introduction

The efficient use of limited resources is increasingly important in environmental and energy-related challenges. This becomes particularly evident in the case of electric vehicles (EVs), which require drivers to manage the limited energy stored in the battery in real-time. At the same time, the transport sector represents one of the most significant contributors to greenhouse gas (GHG) emissions and energy consumption in the European Union. It is responsible for around one-quarter of total EU GHG emissions and consumes over one-third of final energy across European countries (European Environment Agency (EEA), 2024c). Road transport is the dominant source within the sector, accounting for 73.2% of all transport-related emissions in 2022, with passenger cars alone contributing approximately 13% of total EU GHG emissions (European Court of Auditors (ECA), 2024; European Environment Agency (EEA), 2024a). The growing relevance of road transport for climate-neutral mobility has made it a central subject of contemporary research, including technological studies on energy and emission performance, as well as structural, economic, and political analyses of the conditions shaping their integration into the transport system (e.g., Ali et al., 2017; Georgatzi et al., 2020; Haas & Sander, 2020; Haasz et al., 2018; Marrero et al., 2021). Emission levels have shown a limited decline since 2005 despite policy and technological interventions (European Environment Agency (EEA), 2024a). This underscores the need for effective mitigation strategies to meet the EU's 2050 climate neutrality objective (European Commission, 2019; European Parliament and Council, 2021). One of the EU's central responses to this challenge is the decarbonisation of road transport through the transition to electric powertrains (European Environment Agency (EEA), 2024b). Electric vehicles (EVs), particularly battery electric vehicles (BEVs), are expected to play a central role in this transition. While the full emission reduction potential of vehicle electrification is projected to unfold in the coming decades under scenarios involving high shares of grid-connected EVs (Haasz et al., 2018), EVs made up nearly 23% of new passenger car registrations in Europe in 2023, with BEVs alone accounting for 15% (European Environment Agency (EEA), 2024b). Several studies have shown that BEVs significantly reduce GHG emissions, mainly when powered by low-carbon electricity (Bouter et al., 2020; Canals Casals et al., 2016; Da Costa et al., 2025; Kumar, 2024; Zhang et al., 2024), with particularly high energy and CO<sub>2</sub> savings in urban driving contexts (Rolim et al., 2012).

However, the climate benefits of BEVs are not solely determined by advancements in drivetrain technology (Wahid et al., 2021) or electricity sources (e.g., Rapa et al., 2020). Actual energy consumption depends mainly on how vehicles are driven, highlighting the drivers' critical role in adapting their behaviour to EV-specific energy dynamics. Along with the finding that actual energy savings largely depend on driver behaviour regarding ICEVs (Barkenbus, 2010), an energy-efficient driving style further enhances BEVs' environmental benefits with 7–18%

reduced CO<sub>2</sub> emissions (Kubik et al., 2023; Opetnik et al., 2024). Combining an energy-efficient driving style with large-scale BEV adoption and optimised fleet management strategies further improves these benefits (Kubik et al., 2023; Kumar, 2024). Beyond their broader environmental effects, energy-efficient driving behaviours also offer individual benefits, including economic savings, support for altruistic and environmental motives, and increased competence when managing low-battery situations (Barkenbus, 2010; Bingham et al., 2012; Franke et al., 2017; Günther et al., 2019; Kramer & Petzoldt, 2023; Rolim et al., 2012; Schießl et al., 2013).

While energy-efficient driving behaviour can be theoretically defined and precisely calculated based on physical models like economic adaptive cruise control (Jia et al., 2019; Weißmann et al., 2017), the actual behavioural implementation poses substantial cognitive demands on drivers' action regulation. Drivers must regulate their actions in real-time, often under uncertainty, and adapt to system properties that differ substantially from those of conventional internal combustion engine vehicles (ICEVs). The energy dynamics of EVs lead to additional cognitive and perceptual challenges, as they are embedded in an already complex primary driving task, comprising more than 1,600 subtasks (Franke et al., 2016; Neumann et al., 2015; Walker et al., 2001; Young et al., 2011). Strategies known and automated in the context of ICEVs (e.g., early upshifting, rapid accelerations) are no longer applicable or lead to energy losses in EVs, which is also reflected in false beliefs about energy efficiency (Beusen et al., 2009; Franke et al., 2016; Franke, Görges, et al., 2019; Neumann et al., 2015). In addition, regenerative braking—as an EV-specific behavioural strategy—has a significant impact on both the driving task and energy efficiency, as it requires anticipatory driving, adapted pedal interaction, and reflective use to minimise conversion losses (e.g., Cocron et al., 2013; Franke, Görges, et al., 2019). Unfamiliar metrics or indicators such as kilowatt-hours, ampere-hours per 100km, or percent state-of-charge units are potentially less intuitively linked to driving actions and understanding than familiar ICEV units and fuel gauges (Neumann & Krems, 2015; Strömberg et al., 2011). Against this background, drivers must develop new mental representations of energy consumption and efficiency.

Thus, the central question is how the human-system interface must be designed to facilitate effective action regulation and to be experienced as both supportive and facilitating comprehension. From a psychological perspective, this requires considering fundamental principles of human information processing, including bounded rationality, heuristics, and biases in perceiving and evaluating driving-related information (Eriksson et al., 2015; Franke, Görges, et al., 2019; Herberz et al., 2019; Kahneman, 2003; Moll & Franke, 2021; Simon, 1982; Svenson, 2021; Tversky & Kahneman, 1973, 1974). Ecodriving feedback should enable appropriate interpretations by supporting a situation-specific understanding (i.e., *situational model*, Baumann & Krems, 2007, 2009; Endsley, 2000) based on an adequate, action-relevant

*mental model* of energy-efficient driving with its boundary conditions and underlying energetic reasoning (Carroll & Olson, 1988; Sureth et al., 2019; Zacher & Frese, 2018). These representations are crucial for effective action regulation, as they enable drivers to understand causal relations between their behaviour and its consequences and to transfer strategies across contexts flexibly (Osman, 2010). Conversely, mismatches between subjective experience and actual mental representations may lead to uncertainty, a reduced sense of competence, or selective information processing (Bland & Schaefer, 2012; Enke & Graeber, 2019; Leung, 2020; Schaub, 2006).

Despite these psychological requirements, current feedback approaches often fail to support such representations and effective action regulation in practice, along with general challenges in designing energy-efficiency interfaces (Franke, G6rges, et al., 2019). With current displays (e.g., instant consumption), it seems complicated to derive the efficiency potential—even for highly motivated drivers—and inefficient strategies are developed (Arend et al., 2019; Franke et al., 2016). It has also been shown that manageable improvements can be achieved at the performance level (e.g., Martin et al., 2013), and existing knowledge does not necessarily influence the actual strategies used (e.g., McIlroy & Stanton, 2017; Pampel et al., 2015). Whether commonly used feedback designs are sufficient to support effective energy-efficient driving remains questionable, making it essential to look at the current research on different informational approaches. Overall, onboard feedback systems have emerged as a promising approach to promote more energy-efficient driving behaviour and have been studied primarily in the context of ICEVs (e.g., Allison et al., 2021; Beloufa et al., 2019; Sanguinetti et al., 2020). Feedback on energy-efficient driving can lead to moderate but consistent reductions in fuel consumption, with an estimated average improvement of 6.6%–9.0% in fuel efficiency with highly varying effects up to 30–35%—likely due to differences in methodology and feedback designs (Dahlinger & Wortmann, 2016; Kurani et al., 2015; Sanguinetti et al., 2020). However, Dahlinger et al. emphasised substantial methodological limitations in the body of past research, including small sample sizes, non-reported methodological information on the kind of feedback or intervention period, designs that did not allow for causal inference, or often measuring consumption at insufficient temporal resolution (Dahlinger, Wortmann, et al., 2018; Dahlinger & Wortmann, 2016). They concluded that past studies rarely achieved the minimal standard of methodological quality. Moreover, ecodriving with BEVs has seldom been investigated (Heidinger et al., 2023), and many interventions lacked theoretically or psychologically grounded manipulations, particularly regarding differentiated degrees of automation (Parasuraman et al., 2000; Wickens et al., 2010). As a result, underlying assumptions about information processing stages and the role of comprehension in feedback processing are often neglected or insufficiently theorised. For example, it is still unclear whether currently prevalent less automated consumption feedback, which has rarely been studied (Dahlinger & Wortmann,

2016), enables drivers to develop accurate judgements of energy efficiency for forming and applying effective behavioural strategies.

In sum, BEV driving constitutes a psychologically relevant form of resource regulation and an informative research context for applied and engineering psychology. Here, behavioural decisions and performance can be directly and continuously linked to energy outcomes. This makes it possible to systematically examine how users adapt and self-regulate under real-world constraints and how different types of human–system coupling influence underlying cognitive mechanisms, such as information processing in decision-making, the development of mental representations, and the perceived support of action regulation and comprehension. These considerations converge on a central design challenge: achieving optimal alignment between system characteristics, associated demands, and human information processing capacities. In the context of energy-efficient driving, this involves not only considerations regarding the timing and content of feedback but also the systems' degree of automation, as it can yield both beneficial and adverse effects (Onnasch et al., 2014; Parasuraman et al., 2000; Tataschiere et al., 2020; Wickens et al., 2010). Importantly, the benefits and costs of automation are not universal, but rather system- and context-dependent and must therefore be systematically evaluated and compared across different types of ecodriving feedback approaches (Parasuraman et al., 2000; Ruscio et al., 2024; Wickens et al., 2010). Addressing these questions is a core objective of user-centred system design in applied and engineering psychology (Haslam & Waterson, 2013; McIlroy et al., 2014; Revell et al., 2018).

The objective of the present dissertation is to advance engineering psychology in the context of ecodriving feedback systems for BEVs by addressing various facets of adaptive ecodriving control that identify (cognitive) challenges and evaluate how different feedback approaches can effectively address them. First, this research will systematically analyse the cognitive demands of energy-efficient driving in BEVs, with a particular focus on potentially biased efficiency judgements and misconceptions that may distort drivers' decision-making. Second, it will evaluate the extent to which different ecodriving feedback approaches affect objective driving performance. Third, it will investigate drivers' patterns and gaps in their accessible knowledge, and assess whether different feedback approaches enhance perceived understanding. Finally, the dissertation will explore drivers' perceived support of action regulation and *mental model* by the system as key human factors influencing how feedback is experienced in terms of task demands and perceived capability. By addressing these gaps, this dissertation aims to provide evidence-based recommendations for ecodriving feedback that integrate the goal of energy reduction with psychological principles of human information processing and *mental model* development. The research contributes to advancing the theoretical and applied knowledge in engineering psychology, ultimately supporting efforts toward more sustainable mobility.

The current dissertation comprises a synopsis and four empirical studies, including one first-author publication and three unpublished studies. In the first part of the synopsis, I present the theoretical background necessary to understand the cognitive mechanisms and demands underlying drivers' interaction with ecodriving feedback while regulating energy-efficient behaviour. Section 2 provides an overview of adaptive control in ecodriving and key psychological theories and concepts relevant to energy-efficient driving (2.1), the role of *mental models* in supporting energy-efficient driving behaviour (2.2), a systematic literature search on ecodriving feedback research (2.3), and automation in ecodriving feedback approaches (2.4). Thereby, the theoretical foundation is laid and research gaps are identified that motivate the research objectives (ROs) presented in Section 3. In Section 4, I summarise the four empirical studies included in the dissertation and outline their specific contributions to the ROs. Sections 5 through 8 present the studies in detail, each employing either qualitative or quantitative methods to examine different feedback approaches and their psychological effects. The general discussion in Section 9 constitutes the second part of the synopsis. It integrates the findings, discussing their theoretical implications in light of the ROs (9.1), critically reflecting on the methodological approach (9.2), and outlining the overall contribution to the field of engineering psychology (9.3). The dissertation ends with a short conclusion in section 10.

## 2. Theoretical Background

This chapter provides the theoretical foundation for investigating how different feedback approaches influence users' perception, understanding, and regulation of energy-efficient driving. Section 2.1 outlines the concept of adaptive control in ecodriving, distinguishing between control theories and action regulation theory, and introducing relevant models such as the three levels of human performance, the *Task-Capability Interface* (TCI) model, and the *Comfort-Zone model* (CZM). Section 2.2 focuses on the role of mental representations, clarifying the construct of *mental models* in contrast to related concepts and summarising prior research on *mental models* in ecodriving, including challenges in capturing them empirically. Section 2.3 reviews existing ecodriving research based on past meta-analyses and reviews, complemented by a systematic literature search to identify current research gaps. Finally, Section 2.4 introduces relevant perspectives on human interaction with automation that are also critical for understanding user–system dynamics in the context of ecodriving feedback.

### 2.1. Adaptive Control of Ecodriving

The term *ecodriving* is commonly used to refer to energy-efficient driving behaviour, though the specific behaviours it encompasses vary across research contexts and perspectives. Sivak and Schoettle (2012) proposed a broad and frequently cited framework that distinguishes between three levels of driver decisions: strategic, tactical, and operational. Strategic decisions involve considerations such as selecting an energy-efficient vehicle or maintaining optimal tire pressure. Tactical decisions relate to planning aspects of the trip, like selecting route types or dealing with congestion. In contrast, operational decisions refer to real-time vehicle control, including acceleration, braking, and speed regulation, but also the use of cruise control or the air conditioner. Complementing this framework, Kurani et al. (2015) define ecodriving as any driver action that improves energy efficiency within the technical constraints of a specific vehicle. Sanguinetti et al. (2017) further elaborate a behavioural taxonomy of ecodriving, distinguishing between six classes, with *driving* as a direct vehicle operation being the most relevant for real-time energy use. It includes behaviours such as accelerating, cruising, decelerating, parking, and anticipating traffic, and typically involves manipulating vehicle controls like pedals, steering, or driving mode selection. This class closely aligns with the operational level of Sivak and Schoettle (2012). This dissertation focuses specifically on operational driving behaviour as it unfolds in real-time, rather than on upstream planning or long-term decisions—consistent with prior work that has examined drivers' interaction patterns with energy-relevant vehicle systems (e.g., regenerative braking, driving modes), the impact of feedback and training interventions on driving efficiency, and the relationship between control strategies and fuel or energy consumption (e.g., Arend & Franke, 2017; Cocron et al., 2013;

Sureth et al., 2019; Wu et al., 2017). In BEVs, such behaviours have immediate consequences for energy consumption and range, making them a critical target for behavioural analysis and interface design. A more detailed overview of previous ecodriving research is provided in Section 2.3.

From a behavioural perspective, ecodriving behaviour encompasses both steering and longitudinal control and is not merely a set of discrete actions but reflects a continuous regulation process that is not random or reflexive but rather deliberate, goal-directed efforts to manage vehicle motion efficiently. This view is consistent with control-theoretic models of behaviour (Carver & Scheier, 1982; Powers, 1973), also in the context of driving (Franke et al., 2016; Franke & Krems, 2013; Fuller, 2011; Macadam, 2003; Mole et al., 2019; Nash et al., 2016; Summala, 2007). These models describe (driving) behaviour as a continuous regulation process involving feedback loops between perceived states and intended outcomes. Macadam et al. (2003) emphasise that treating the driver and vehicle as an integrated control system is essential.

Thus, the models by Rasmussen (1983), Sivak and Schoettle (2012), and Michon (1985) provide a structural framework for categorising driving behaviour across different levels of behaviour, while other models complement this perspective by focusing on dynamic aspects such as situational regulation, motivational control, and potential mismatches between task demands and driver capabilities (Carver et al., 2015; Carver & Scheier, 1982, 1998, 2000; Frese & Zapf, 1994; Fuller, 2005, 2011; Powers, 1973; Summala, 2007; Zacher & Frese, 2018). To deepen this understanding of ecodriving as a dynamic regulation process, the following sections examine a set of complementary theoretical frameworks that offer insights into both the structure and dynamics of driver behaviour. Together, these perspectives provide a differentiated foundation for understanding how ecodriving demands interact with drivers' capabilities and effort, and how feedback systems can support or hinder energy-efficient behaviour at different levels of control and decision-making.

### **Control versus Action Regulation Theory**

Human action is generally understood as goal-directed behaviour, which is influenced by both stable and dynamic personal factors, such as personality, orientations, and affective states, and information from the physical and social environment (e.g., Aarts & Elliot, 2012; Hacker, 1985; Hommel, 2022; Schutz, 1991). Carver and Scheier's (1982, 2000) self-regulation theory provides a comprehensive model of how individuals control their behaviour to pursue their goals, drawing on principles from cybernetics and control theory (Miller et al., 1960; Powers, 1973; Wiener, 1948). At the core of this model lies a negative feedback loop that functions to

minimise the discrepancy between the current state and the desired goal. The feedback loop comprises four key elements: (1) an input function, which perceives the current state; (2) a reference value, representing the desired state (i.e., goal); (3) a comparator, which compares the current state to the reference value; and (4) an output function, which is the behaviour aimed at reducing the discrepancy. The feedback process operates iteratively, where the output behaviour impacts the environment, leading to a change in the present state. This is then compared again with the goal, serving as the reference value. If a discrepancy is found, behaviour is adjusted to close the gap. This feedback cycle continues until the desired state is achieved. These processes are fundamental in guiding human action, ensuring that goal pursuit remains adaptive and responsive to changing conditions. While the typical feedback loop reduces discrepancies, Carver and Scheier (2000) also acknowledge the existence of discrepancy-enlarging loops, which instead increase deviations from the reference point (e.g., socially inconsiderate driving behaviour as anti-goal). These two loops, driven by approach and avoidance motivations, illustrate the broader control mechanisms that influence behaviour. Carver and Scheier also conceptualise a parallel affect loop that directly influences what happens in the control loop of behaviour (Carver et al., 2015; Carver & Scheier, 1998). The discrepancy signal in the behavioural loop is also subjectively experienced as a positive or negative affect. Positive affect indicates that the individual is doing better than expected, while negative affect signals that greater effort is needed to close the gap. Negative affect signals that the discrepancy requires immediate attention, whereas positive affect allows for the temporary downgrading of the priority of that goal (Carver et al., 2015; Simon, 1967).

The authors further differentiate different levels of abstraction and thereby “be”-goals at high levels of abstraction (e.g., being an environmentally conscious person) that are defined based on principles (i.e., values, morals) and goals at lower levels of abstraction. These might be “do”-goals (e.g., driving energy-efficiently) or motor control goals (e.g., avoiding full-throttle) and involve particular behaviours (Carver & Scheier, 2000) that are understood as autonomously runned brief *sequences* of action as well as *programs* (Powers, 1973) or *scripts* (Schank & Abelson, 1975). Later work discusses the compatibility with dual-process models and differentiation between planful, effortful, top-down processing (reflective, deliberate control) and more autonomously triggered well-learned action sequences (reflexive processing; Carver et al., 2015).

Franke et. al. (Franke et al., 2016; Franke & Krems, 2013) extend control-theoretic models of self-regulation (e.g., Carver & Scheier, 1982; Fuller, 2005; Summala, 2007) to the selection of energy-efficient strategies and range management. Their frameworks conceptualise ecodriving behaviour as an adaptive, feedback-driven regulatory process to minimise discrepancies between perceived states and internal reference values. In the context of strategy selection,

drivers select and implement behavioural strategies based on the perceived strategy effectiveness (i.e., judgements of strategies' energy efficiency) and subjective expected utility. In range management, drivers appraise the current state (e.g., available range buffer) with internal reference values or thresholds (performant, competent, or comfortable range). Reference values, evaluation (e.g., range appraisal, strategy effectiveness), and target intensity are shaped by individual differences such as driving experience, trait variables, motivation, and knowledge. Finally, the authors assume knowledge- and experience-dependent accuracy of perceived strategy effectiveness and automation of behavioural regulation.

Critically, it must be noted that, according to Mansell and Marken (2015), Carver and Scheier misrepresented fundamental aspects of *Perceptual Control Theory* (PCT), as initially proposed by Powers (1973). Specifically, they argue that Carver and Scheier incorrectly portrayed behaviour, rather than perception, as the central target of control. This distinction is crucial: in PCT, behaviour is not controlled directly but emerges as a means to maintain perceptual variables at reference levels, based on a continuous negative feedback process. In this light, ecodriving involves ongoing perceptual regulation (e.g., of perceived pedal position or instant consumption) in response to dynamically changing environmental inputs.

Furthermore, control theories assume relatively stable goals and do not account for the active formation, revision, or escalation of goals over time (Zacher & Frese, 2018). *Action Regulation Theory* (ART; Frese & Zapf, 1994; Zacher & Frese, 2018) builds on these foundations and extends them. First, it includes both negative and positive feedback processes, meaning individuals not only reduce discrepancies, but also proactively create new ones by setting more ambitious or complex goals (e.g., expert strategy pulse and glide complementing previous driving strategy to keep inertia in the ecodriving context). Second, ART highlights processes such as active planning, pre-feedback, and developing expertise—dimensions that control theory largely omits. Third, while both theories assume hierarchical levels of regulation, ART explicitly theorises the dynamic interplay between these levels, including how automated routines and conscious strategies interact during learning and adaptation. Notably, ART conceptualises hierarchy not primarily in terms of goal abstraction (see Carver & Scheier, 1982, 2000) but in terms of the structure of the entire regulation process. Building on this foundation, ART conceptualises the *action process* as a structured sequence consisting of five core steps: (a) development and selection of goals, (b) orientation including prognosis of future events, (c) generation of plans and decision to select a particular plan from available plans, (d) execution and monitoring of the plan, and (e) feedback processing (Frese & Zapf, 1994; Zacher & Frese, 2018). Regulation can occur at four different levels. At the first level, automatic sensorimotor routines, regulation includes highly automatised movement patterns, stereotypic routines, and non-physical cognitive automaticities (e.g., steering and lane keeping). The second level,

flexible action patterns, is characterised by rule-based information processing based on *schemas* or *scripts* (e.g., maintaining a steady speed in stop-and-go situations). At the third level, intellectual or conscious regulation, individuals apply effortful, attention-demanding problem-solving strategies for complex or novel actions (e.g., driver decides to switch on the ecomode and glide neutrally more often due to critical remaining range). Finally, the fourth level operates at a heuristic or meta-level, involving meta-cognitive templates, strategies, and abstract heuristics. For example, a driver may reflect on patterns observed across multiple trips, such as high energy consumption variations in urban traffic, and develop a general strategy to compensate for this in future journeys (e.g., by choosing a lower maximum speed on the motorway following particularly inefficient city driving). These levels differ in two dimensions—conscious thought to automated, unconscious behaviour and thought processes to muscular action—and are not only hierarchically ordered but also dynamically interact. With increasing experience and redundancy in the environment, regulatory focus tends to shift from conscious to automated levels, allowing for more efficient, more effortless, and situation-specific action execution. Conversely, in unfamiliar or error-prone contexts, individuals move up the hierarchy to understand why an action is done (Frese & Zapf, 1994).

In line with conceptualisations of Franke et al. (Franke et al., 2016; Franke & Krems, 2013), ART highlights the role of knowledge, expertise, and prior experience as prerequisites for successful action regulation. Knowledge structures guide orientation and planning, while experience allows individuals to recognise meaningful patterns, understand relevant signals, and automate complex sequences. Adequate, detailed, and accurate *mental models* of the goal and its constraints are seen as fundamental for both efficiency and effectiveness in action (Frese & Zapf, 1994; Zacher & Frese, 2018), a role that will be examined in greater detail in Section 2.2.

### **Three Levels of Human Performance**

Rasmussen's (1983) framework of skill-based, rule-based, and knowledge-based levels of human performance offers a differentiated model for understanding and predicting driver behaviour across different situations, depending on whether the task involves highly practised routines or complex problem solving. Originally developed to address performance reliability and error modes in highly automated systems, this taxonomy remains especially relevant where human interaction with complex, dynamic environments, such as road traffic, is critical. Rather than conceptualising humans as mere input–output systems, Rasmussen emphasises the goal-oriented nature of human behaviour: individuals actively define goals, seek relevant information, and select behavioural strategies accordingly. This intentionality becomes particularly apparent when dealing with complex or time-critical situations, for instance, during frequent driving decisions and rapid manoeuvres, where the human sensory system cannot

provide timely feedback for direct correction. In such cases, successful action patterns are often retrieved and adapted from previously internalised routines. These patterns rely on structured internal representations of the system and its dynamics, allowing for anticipatory behaviour and context-sensitive regulation. This insight aligns with principles from ART (Frese & Zapf, 1994; Zacher & Frese, 2018), which similarly posit that effective action depends on the availability and adequacy of mental representations. Human adaptability in complex settings, such as driving, is mainly attributable to the breadth and flexibility of these internal representations, which can be generated or modified in real-time based on perceived system constraints and goals.

Rasmussen's model distinguishes three qualitatively different levels: skill-based, rule-based, and knowledge-based behaviour. Skill-based behaviour refers to automated, sensorimotor routines executed without conscious control. Once an intention is set (e.g., keeping a steady speed), the behaviour unfolds as integrated, prototypical spatiotemporal patterns—such as steering through a curve or modulating speed on a flat road. Feedback is minimal at this level, and control is exercised through well-practised perceptual-motor couplings. Occasional top-down modulation can occur, such as when a driver consciously recalls that the road may be slippery due to snowfall, adjusting their behaviour accordingly.

Rule-based behaviour involves actions guided by stored *rules*, which may have been acquired through experience, social learning, or explicit instruction. For example, a driver may follow a procedural rule: “If the speed limit drops ahead, then I release the throttle pedal early instead of braking.” This level is characterised by anticipatory control (feedforward), where performance is shaped by expectations rather than immediate feedback. Crucially, feedback is only integrated if the individual fully understands the system's response.

Knowledge-based behaviour emerges in novel or unpredictable situations, such as when the remaining range drops unexpectedly and no familiar rule seems applicable. In such cases, the driver formulates explicit goals and develops a strategy through conceptual reasoning. Potential action plans are internally simulated and evaluated, drawing on an explicit *mental model* of the system's structure and dynamics. This process requires declarative knowledge and cognitive capacity for problem-solving and forecasting outcomes based on causal understanding.

A critical implication of this hierarchy for feedback design is that no single level of feedback suffices across all driving contexts. While real-time sensory cues may be appropriate for guiding skill-based behaviour (e.g., haptic pedal feedback), supporting driving novices or energy-efficient driving in complex situations requires interventions at higher cognitive levels. Feedback systems should therefore be tailored to enhance rule- and knowledge-based performance by: Facilitating the development of *mental models* concerning energy flows, system

states, and environmental contingencies; Presenting energy-efficiency information in a form compatible with the driver's level of processing—differentiated into signals (immediate cues such as tracking a set point for maximum speed at motorways), signs (interpretive rules like an ecoscore reflecting acceleration intensity), and symbols (abstract system representations such as visualisations of energy loss sources like rolling resistance or aerodynamic drag).

### **Task-Capability Interface Model**

From a control-theoretical perspective, Fuller's TCI model also conceptualises driving as a dynamic regulation task, in which driver behaviour emerges from the continuous balancing of perceived task demand and available capability (Fuller, 2005, 2011). Task demand arises from environmental factors such as road alignment, other road users, and operational features of the vehicle (e.g., ecodriving displays, ecodriving modes). Perceived capability is shaped by basic biological characteristics (e.g., information processing capacity) and acquired characteristics through experience and training (e.g., knowledge, skills). The actual level of capability is constrained by performance-restricting factors like attitude, motivation, fatigue, stress, and distraction. The perceived difficulty of the driving task reflects the momentary ratio between these two variables. A core proposition of the TCI model is that drivers attempt to maintain a subjectively acceptable level of task difficulty by adapting control strategies such as speed, headway, or lane position. When demand exceeds perceived capability, drivers typically slow down or increase following distance to reduce cognitive and physical strain. Conversely, when the task feels too easy, they may increase speed or engage in secondary tasks to avoid underload. This self-regulatory mechanism—often described as task difficulty homeostasis—suggests that driving behaviour is not solely reactive to environmental constraints but also shaped by self-regulatory preferences for optimal challenge. The emphasised dependence of driving regulation on interindividual differences (attitude, knowledge, motivation) is in line with frameworks of Franke et al. (2016), Franke and Krems (2013), and Frese and Zapf (1994).

In ecodriving at the tactical (manoeuvring) and operational (control) levels (Michon, 1985), control of behaviour is not limited to choosing a specific target speed, but also includes how drivers manage transitions between different speeds over time—that is, how they accelerate and decelerate in energy-efficient ways. Nevertheless, perceived task demand and, particularly, perceived capability are critical for controlling energy-efficient behaviour.

### **Comfort-Zone Model**

Also building on control-theoretic frameworks of driver behaviour, Summala (2007) introduced a motivational-emotional perspective through the concept of *comfort through satisficing*. Rather than striving to maximise efficiency or minimise risk, drivers tend to maintain their behaviour within a personally acceptable range of comfort and effort. This satisficing principle aligns with Simon's (1955) theory of bounded rationality, suggesting that individuals choose the first option that meets an acceptable threshold rather than optimising across all alternatives.

This idea is central to the CZM, which emphasises a unique control approach centred on spatial and temporal *safety margins* (Summala, 2007). These margins (e.g., time-to-collision, distance to potential hazards) are key regulatory variables. Drivers seek to maintain these safety margins within a comfort zone, the violation of which triggers discomfort or negative affective states, thereby prompting corrective behaviour. Consequently, everyday driving rarely involves strong emotional states such as fear or anxiety, as behaviour is typically regulated to remain within these self-imposed bounds of comfort (Summala, 2007).

Parallels can be drawn to Carver and Scheier's (1982) *affect loop*, in which deviations from internal reference states elicit emotional responses that guide self-regulation. This suggests that discrepancies from one's comfort zone—like due to recommended ecodriving behaviours that increase task difficulty or provoke a critical reassessment of one's previously perceived capability (see Fuller, 2005, 2011)—generate affective signals that help maintain a certain margin in the homeostatic loop. As Goodrich et al. (2000) elaborate, skills as learned simple or complex action sequences provide affordances that are evaluated based on their context-dependent benefits and costs (attractive vs. repulsive potential). This trade-off process underlies satisficing behaviour, where the chosen option is not the optimal but the sufficiently good alternative given context-specific constraints. Thus, ecodriving is not always pursued as a primary goal, especially when the associated task demands are perceived as uncomfortable or misaligned with situational constraints and one's perceived knowledge or driving skills. In such cases, the intensity of related target values may be attenuated. Thus, besides competing motives (e.g., time pressure, driving enjoyment, safety), ambiguous, overwhelming, or delayed feedback can foster frustration and lead drivers to deprioritise energy efficiency in favour of comfort and cognitive ease.

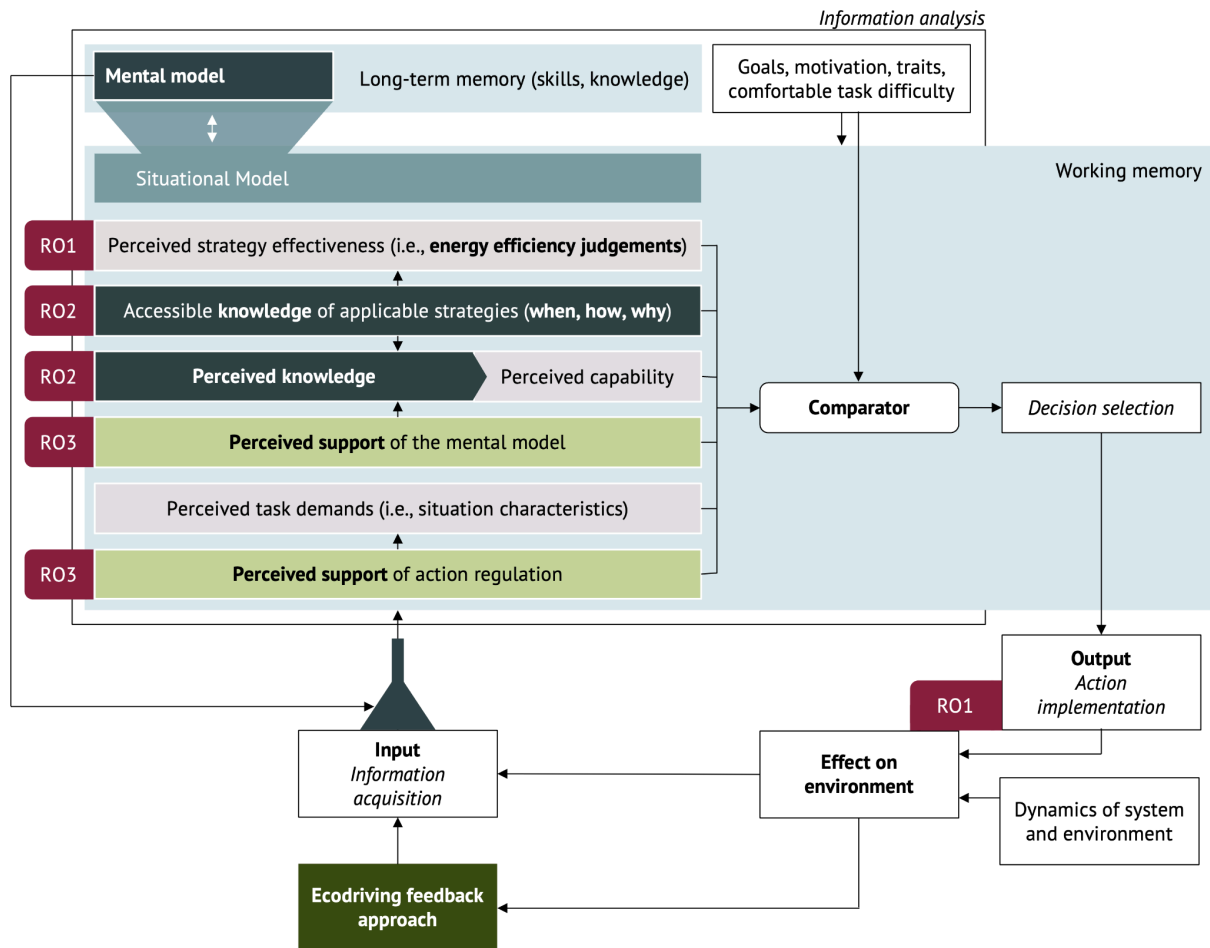
### **Implications for the Adaptive Control of Ecodriving through Feedback Approaches**

Various (control-theoretical) models of human behaviour (Carver et al., 2015; Carver & Scheier, 1982, 2000; Franke et al., 2016; Frese & Zapf, 1994; Fuller, 2005, 2011; Rasmussen, 1983; Zacher & Frese, 2018) emphasise the central role of internal mental representations (i.e.,

*mental models*) and the resulting perceived capability and strategy effectiveness (i.e., energy efficiency judgements) in enabling effective, efficient and comfortable action regulation under task demands shaped by situational constraints. In the general conceptualisation of adaptive control of ecodriving behaviour (see Figure 1), ecodriving is thus understood as dynamically regulated behaviour across conscious to automated levels. In line with Rasmussen (1983), highlighting the need to consider “human mental functions”, human information processing stages are more detailed within the control loop.

**Figure 1**

Adaptive Control of Ecodriving Behaviour



*Note.* Conceptualisation is primarily based on Carver and Scheier (1982), Wickens (2015), Wickens and Carswell (2021), Endsley (2000), Fuller (2005, 2011) and Franke et al. (2016). Information processing stages are formatted in italics. RO = research objectives.

Within the ART framework (Frese & Zapf, 1994; Zacher & Frese, 2018), ecodriving feedback approaches can be interpreted as external signals (i.e., input) that facilitate or hinder effective regulation. From an ART perspective, the effectiveness of such signals depends on their number, differentiability, transparency (i.e., understanding the meaning), consistency, active search, and predictability. Feedback at the intellectual or conscious level comprises the analysis and combination of novel and complex information. Thus, novices may need more explicit and interpretive feedback, whereas experts can more readily integrate minimal cues into existing *schemas*, triggering efficient routines. Therefore, ecodriving feedback approaches should be tailored to drivers' competence levels and embedded within an architecture that supports low- and high-level regulation.

Also, the TCI framework (Fuller, 2005, 2011) implies that ecodriving feedback approaches must be calibrated to drivers' perceived capability. Approaches that align with existing knowledge structures and support anticipatory strategies can reduce subjective difficulty and enhance control. For example, displays that help drivers anticipate regenerative braking opportunities or upcoming gradients can facilitate proactive energy management. In contrast, feedback systems that overwhelm or conflict with the driver's perceived knowledge (gaps) may be ignored or misunderstood, especially if they increase the cognitive load without clear benefit. For example, drivers may lack the knowledge to translate feedback into specific actions if confronted with a 50/100 ecodriving braking score. If they don't understand why and how exactly they should improve their driving, they lack the concrete behavioural framework needed to use the feedback. In that case, they don't perceive it as helpful information. Another relevant example is that novice drivers might be overwhelmed by technical visualisations like the engine's efficiency map. Such detailed representations that show the complex relationships between driving behaviour and energy conversion efficiency can lead to cognitive overload, especially if the drivers do not have the knowledge or experience to interpret these details correctly. In such cases, the drivers will likely either ignore or misunderstand the feedback, and capability will be perceived as being too low compared to the perceived task demands (Fuller, 2005, 2011).

In sum, the effectiveness of a feedback approach in promoting energy-efficient behaviour depends not merely on its content or modality, but on its alignment with the driving situation's complexity and the driver's mental representations available. Efficiency-related feedback must therefore be evaluated based on its ability to foster accurate perceptions or judgements of strategy effectiveness, increased perceived knowledge, and to support effective, efficient, and confident action regulation. This includes not only real-time guidance but also the perceived support of mental representations that enable anticipatory control. Crucially, drivers differ in how they perceive and calibrate their ecodriving capabilities. Overestimating one's knowledge or underestimating the complexity of energy-efficient regulation can lead to operating near the

limits of actual capacity (Fuller, 2011), resulting in ineffective strategy use or disregard of system feedback. Accordingly, a differentiated understanding of perceived and actual ecodriving knowledge or strategy effectiveness is essential. Against this backdrop, it becomes evident that actual mental representations and perceived knowledge shape how drivers interpret, evaluate, and act on feedback in dynamic driving contexts. The following section examines their role in more detail, drawing on theoretical models and empirical findings to clarify how *mental models* guide attention, inform judgments, and ultimately support adaptive ecodriving regulation.

### 2.2. Role of Mental Models

In many domains of human-technology interaction, including energy-efficient driving with BEV, safe and effective use depends on a correct understanding of the system and its functioning. Such internal representations are commonly referred to as *mental models*, the definition of which varies across research disciplines. For this dissertation, the definition by Carroll and Olson (1987, p. 12) is adopted, who describe a *mental model* as “a rich and elaborate structure, reflecting the user’s understanding of what the system contains, how it works, and why it works that way. It can be conceived as knowledge about the system sufficient to permit the user to mentally try out actions before choosing one to execute.” Durso and Gronlund (1999) further emphasise the knowledge about causal interconnections involving actions and environmental factors that influence a system’s functioning. These internal representations enable individuals to interpret environmental cues, comprehend system states, and project likely future developments (Endsley, 2012). This is particularly relevant in the complex driving context while anticipating how vehicle dynamics (e.g., acceleration, regenerative braking) interact with environmental features such as terrain or traffic conditions. Here, rule-based knowledge directly explicates input–output relationships and enables flexibility and transfer to perceptually or structurally different situations by creating representations of structural properties of driving strategies (Osman, 2010).

In general, available and adequate mental representations are essential for forming consistent and coherent *situational models* and thereby successfully regulating goal-directed behaviour (Baumann & Krems, 2009), especially in dynamic and cognitively demanding tasks such as energy-efficient driving. According to Endsley (2000), the *situational model* represents a dynamic instantiation of the *mental model*, depicting the user’s current understanding of the system’s present state.

Unlike the relatively stable, generic long-term knowledge contained in the *mental model*, the *situational model* is continuously updated through perception and cognition (Endsley, 2000; Wickens, 2015). In line with Baumann and Krems (2009), it is assumed that perceived

information activates semantically linked knowledge structures in long-term memory, which are then made available in working memory and integrated into the *situational model* (see Figure 1). This ensures that relevant parts of the *mental model* are selectively retrieved and used to build a coherent understanding of the current situation. Thus, the *situational model* is largely shaped by the *mental model* the individual already holds (Endsley, 2000; Wickens, 2015). The latter determines which environmental features are attended to, how they are interpreted, and what future projections are formed, thus influencing all three levels of *situation awareness* (i.e., *situational model*). As such, information that aligns with the *mental model* is more likely to be retained and integrated, while information deemed irrelevant may be discarded (Endsley, 2000). This selectivity enhances cognitive efficiency but can lead to critical oversights if the underlying *mental model* is incomplete or incorrect.

When drivers possess relevant and accurate *mental models*, they can direct their attention toward task-relevant information and integrate sensory inputs more effectively, thereby circumventing the limitations of working memory (Endsley, 2012). For example, recognising a familiar ecodriving feedback or anticipating an upcoming energy-saving opportunity (such as a downhill segment) becomes more intuitive when these elements are embedded within a coherent mental representation of the driving task. Such mechanisms are crucial for advancing from mere perception of environmental elements (Level 1 of *situation awareness*) toward higher-level comprehension (Level 2) and projection (Level 3), which are essential for proactive energy-efficient driving strategies (Endsley, 2012; Wickens, 2015).

Conversely, novice drivers or those operating in unfamiliar settings may lack these elaborated mental representations and thus must rely on working memory and attention-intensive rule- or heuristic-based reasoning (Endsley, 2012). From a cognitive control perspective, this marks a shift from skill- or rule-based performance toward knowledge-based behaviour, as conceptualised in Rasmussen's (1983) taxonomy of human performance. While experienced drivers operating in familiar settings may rely on automated, integrated routines that unfold largely without conscious control (skill-based behaviour), and may even employ stored *rules* or procedures derived from past experiences or instruction (rule-based behaviour), unfamiliar driving contexts—such as vehicles with new energy dynamics, novel ecodriving feedback, or unanticipated terrain—often require a shift to knowledge-based behaviour. In such situations, no pre-existing *scripts* or *know-how* are available, and individuals must engage in conscious goal formulation, plan generation, and hypothesis testing based on a conceptual understanding of system properties. Here, *mental models* become indispensable. According to Rasmussen (1983), knowledge-based behaviour necessitates explicit reasoning about the internal structure and functional properties of the environment, typically represented by a *mental model*. This level of reasoning is particularly relevant for novice drivers or those encountering unfamiliar

ecodriving feedback for the first time, as they must mentally simulate alternative courses of action and predict their outcomes through conceptual analysis or physical trial and error. In such cases, *situation awareness* is closely tied to the initial acquisition of static system knowledge, which forms the foundation for subsequent situational reasoning (Wickens, 2015). The ability to construct, refine, and correct *mental models* in real-time determines the success of action regulation under uncertainty. Moreover, Rasmussen emphasises that effective human cognition depends on continuously transforming and updating *mental models* in response to new input, often occurring below conscious awareness. This dynamic quality aligns with Endsley's (2000) notion of the *situational model* as an evolving instantiation of the *mental model*, shaped through ongoing perception and interpretation. Thus, the interplay between knowledge-based control and *mental model* refinement is critical in driving contexts where established routines fail and adaptive energy-efficient behaviour must be constructed from first principles.

However, this increases cognitive workload and slows decision-making, reducing the ability to respond effectively to time-sensitive, energy-relevant cues. While Pampel et al. (2018) argue that most drivers regulate eco-driving behaviour more consciously and effortfully than their everyday driving routines, eco-driving behaviour can be proceduralised over time. By extracting situational regularities and integrating them into stable *rules* and *schemas*, drivers can gradually shift from knowledge-based reasoning to more automated control modes (Anderson, 1983; Michon, 1985; Rasmussen, 1983). *Mental models* formed through experience can support recognising environmental patterns and link them to well-learned action tendencies, facilitating efficient regulation without overloading cognitive resources (Endsley, 2012).

Importantly, while *mental models* serve as interpretive frameworks that allow drivers to connect and assess the relevance of information, they also pose risks. If a driver relies on an incorrect or incomplete model—such as misjudging the effect of pedal position on neutral gliding or how different braking patterns impact consumption, and misinterpreting feedback from an eco-driving interface—this can result in representational errors (Endsley, 2012). These errors may impair both comprehension and projection, often without the driver being aware of the misalignment. Such errors exemplify how a mismatch between the *mental model* and the actual system state can degrade *situation awareness* and disrupt effective action regulation (Endsley, 2012).

In sum, *mental models* are indispensable for forming and maintaining high levels of *situational awareness* and enabling efficient, anticipatory regulation of behaviour in energy-efficient driving. Their effectiveness lies in reducing cognitive load, guiding attention, integrating information, and supporting accurate inferences—all foundational for both safe and sustainable driving behaviour.

### **Distinguishing Mental Models From Related Constructs**

While *mental models* describe structured internal representations that capture how a system works, including causal mechanisms and dependencies (Carroll & Olson, 1987), other cognitive constructs (i.e., *schemas*, *scripts*, *frames*, *rules*) may guide behaviour in distinct or interacting ways. It must be noted as a limitation that existing distinctions within (control-theoretic) models of behaviour are highly dependent on the underlying definitions and partly vague use of terminology, such as *programs*, *plans*, *scripts*, *rules*, and *schemas*. For instance, Frese and Zapf (1994) differentiate their *action-oriented mental model* or *operative image system* from another definition of *mental models*, which is different from Carroll and Olson's (1987). However, they define their approach very similarly, assuming long-term internal representations of “input conditions, goals, plans, and expected and prescribed results of action, as well as knowledge about boundary conditions of action and the transformation procedures that turn goals into expected results” (Zacher & Frese, 2018, p. 15). More specifically, it “contains unconscious movement schemata, routinised yet flexible action schemata, representations of complex and conscious intellectual processes, and generalised meta-plans and heuristics” (Zacher & Frese, 2018, p. 15). Another example of inconsistently used terms is *plan* seen as an *action program* within the ART in contrast to the term *program* in the PCT (Powers, 1973). Furthermore, some definitions lack explicit cross-references, such as the *schemas* (i.e., *schemata*) in Frese and Zapf (1994). This leads to a lack of fully elaborated integration and differentiation of internal representations within other approaches and information processing, complicating the comparison at the cognitive processing level. Therefore, the following distinctions between other cognitive constructs should not be viewed as an exhaustive representation of the diverse assumptions and definitions, but rather as a framework for understanding the specific role of *mental models* within cognitive processing in the context of the current work.

*Schemas* and *scripts* (Fiske & Taylor, 1991; Schank & Abelson, 1975) organise generalised knowledge about everyday situations, often triggering automatic expectations and responses. Jones et al. (2011) and Katzeff (1990) contrast *mental models* with the construct *schema* in more detail highlighting similarities (long-term structures), differences (e.g., static, inflexible, and generic *schema* vs. dynamic, specific, and flexible *mental model*) and the potential role of *schemas* as initial guide (prior generic knowledge base). From a cognitive systems perspective, Moray (1996, 1997) emphasised that *mental models* are hierarchically organised and operate across all levels of information processing. Referring to previous publications, he described how long-term models may be activated by task demands and intentions (*schemas*), automatically by tasks or environments (*frames*), or with action orientation (*scripts*), and that *mental models* may recursively represent models of other models. Whitney (2001) echoes this view by noting that

constructs such as *schemas* or *frames* serve a similar function as generic representations used in reasoning and interpretation.

By focusing on the definition of Carroll and Olson (1987) and assuming relevance across all levels of information processing, *mental models* can further be distinguished from *rules*. Stored *rules* represent condition–action associations acquired through learning and repeated experience. In Anderson’s *Adaptive Control of Thought–Rational* theory (1983), these are conceptualised as *production rules* in the form of “if X, then do Y,” which are stored in long-term memory and retrieved automatically when the condition is met. Similarly, Rasmussen’s (1983) rule-based level of human performance refers to applying familiar *rules* abstracted from prior experience, typically executed without conscious deliberation. While *production rules* and stored behavioural routines operate largely below the level of conscious awareness in automated decision-making, another class of “if–then” structures—*implementation intentions* (Gollwitzer, 1993, 1999, 2014; Gollwitzer et al., 2010; Gollwitzer & Sheeran, 2006; Sheeran et al., 2025)—represent explicitly formed plans that link anticipated situations to goal-directed behaviours as part of a deliberate self-regulation strategy. These “if–then” formulations are consciously constructed (e.g., “If I accelerate from standstill, then I press the accelerator pedal one-third”), thereby reducing the cognitive demands of action selection during execution. Their primary function is to increase the likelihood of goal-consistent action by specifying the when, where, and how to implement behaviour, particularly under distraction or competing goals. Meta-analytic findings confirm their effectiveness across various behavioural domains (Gollwitzer & Sheeran, 2006; Sheeran et al., 2025). Thus, while stored *rules* emerge through repetition and support efficient behaviour in familiar contexts, *implementation intentions* are strategically employed to preconfigure responses anticipating critical events. Both rely on “if–then” logic, but differ in their origin (implicit vs. deliberate) and how they are accessed and applied: stored *rules* allow for automatic retrieval, whereas *implementation intentions* require preplanned recall and guided execution. *Mental models*, in turn, provide the conceptual scaffolding that supports the acquisition of automated *production rules* and conscious strategic plans that include declarative knowledge. *Mental models* are formed and refined through experience by assimilating new information and adjusting existing structures across different phases, such as identifying system components and their possible states, integrating causal relationships, testing, and running the *mental model* (Katzeff, 1990; Mayer et al., 2002; Moray, 1999). Against this background, it seems plausible that repeated use and understanding of externally provided knowledge in the form of if–then plans may not only bridge the gap between intention and action in the short term (Gollwitzer, 1999). In particular, they may help identify relevant components and states, and highlight causal links between driver behaviour and energy-related outcomes, thereby contributing to the construction and refinement of mental representations in the driving context.

In sum, while related constructs such as *schemas*, *scripts*, and *rules* each play a role in structuring cognition and guiding behaviour in general, this dissertation focuses explicitly on the key construct of *mental models* as dynamic, causally organised representations, and on knowledge-based self-regulatory strategies (e.g., specifying when and how to drive energy-efficiently) that are designed to foster the formation and refinement of such models.

### **Previous Research on Mental Models in Ecodriving**

Existing reviews of *mental models* have focused on human behaviour and decision making as a whole (e.g., Khemlani et al., 2014) or dealt with further developments of the concept of *mental models* (e.g., Johnson-Laird et al., 2015). Existing systematic literature reviews are often very specific in their questions (e.g., *mental models* in teams; Burtscher & Manser, 2012). Overall, there is a scientific consensus that *mental models* are essential for regulating behaviour. Correlations and connections between the quality of *mental models* and behaviour shown are regularly reported (Boelhouwer et al., 2019; Lin et al., 2018; Yu & Wang, 2022). Over time, with increasing experience, the *mental model* seems to approach the ideal *mental model* with a realistic representation of the system functions (Beggiato & Krems, 2013). At the same time, there are several studies where an improvement in *mental models* was not accompanied by significant behavioural changes (Harari et al., 2019; Pradhan et al., 2023). This underlines the need for a precise understanding of the quality and support of *mental models* in the specific context.

Studies in the context of ecodriving focused on behavioural activation or tips and training to improve existing *mental models*. Previous research has emphasised the relevance of internal knowledge structures, particularly *mental models*, for effectively applying ecodriving strategies. While many drivers possess at least rudimentary ecodriving knowledge, they often fail to activate it spontaneously during routine drives (Pampel et al., 2015, 2018). This suggests that ecodriving differs from everyday driving regarding cognitive demands, making it less automatic and more difficult to sustain as a long-term behaviour (Pampel et al., 2018). Studies suggest that supporting *mental model* activation through timely and targeted instructions can improve ecodriving behaviour. For instance, instructions delivered personally and immediately before a drive were more effective in promoting energy-efficient behaviour than general instructions presented earlier (Pampel et al., 2017). Findings from Pampel et al. further suggest that ecodriving competence can deteriorate over time, especially during longer drives or in the presence of competing goals. This underscores the importance of ecodriving feedback that supports cognitive engagement and reinforces forming and consolidating robust *mental models*.

Beyond activation, first efforts have been made to examine and actively improve the structure and quality of (eco)driving *mental models*. Practical experience plays a central role in building and refining *mental models*. Neumann et al. (2015) showed that practical BEV experience was associated with more differentiated knowledge about ecodriving strategies. Proceduralisation effects have also been observed: Helmbrecht et al. (2014) found that factual knowledge gained through driving experience became increasingly integrated into automated behaviour. This aligns with findings from Günther et al. (2019) and Rauh et al. (2020), who identified domain-specific knowledge and practical experience as core components of ecodriving competence and quality of action regulation (e.g., range stress, certainty, acceptance). However, there is evidence that drivers are generally unaware of system functionalities and limitations and tend to obtain only partial information, if at all (Jenness et al., 2008; McDonald et al., 2018; Mehlenbacher et al., 2002). Regarding ecodriving, several false beliefs exist, and technical system knowledge seems to significantly predict fuel efficiency (Arend et al., 2019; Franke et al., 2016). Sureth et al. (2019) demonstrated that ecodriving tips combining *know-how* and *know-why* (underlying rationales) led to significant efficiency gains while generic instructions showed no significant effect. This indicates that promoting causal understanding—i.e., aligning drivers' *mental models* with actual system dynamics—is key to supporting effective strategy use. Similarly, Arend et al. (2019) emphasised the importance of simultaneously structuring feedback interventions to foster behavioural activation and knowledge acquisition. Nevertheless, empirical work explicitly targeting *mental model* development through feedback remains scarce in ecodriving contexts. First evidence shows that even simple, generic ecodriving tips can facilitate change in ecodriving behaviour (Andrieu & Saint Pierre, 2012; van der Voort et al., 2001). Furthermore, the effects on comprehension of ecodriving on the one hand and behavioural change on the other seem to depend differently on the concrete format of intervention and training, such as only static or additional applied training (Wu et al., 2017).

Drivers' *mental models* play a crucial role in interpreting, adopting, and responding to driving assistance systems. If underdeveloped or misaligned with feedback system functionality, this can hinder effective usage and reduce trust and acceptance (Beggiato et al., 2015; Beggiato & Krems, 2013; Victor et al., 2018). Evidence suggests that training, guidance, and explanatory system feedback can support the development of more accurate *mental models*, improve drivers' ability to perceive and evaluate system status (e.g., possible applications of automated driving technologies or energy efficiency), and strengthen their confidence in behavioural control (Beggiato et al., 2015; Feinauer et al., 2023; Orlovska et al., 2024; Pradhan et al., 2023).

The findings underline that effective ecodriving behaviour depends on the structure, accessibility, and accuracy of drivers' *mental models* that can be supported by and must be

aligned with feedback and training interventions, while also considering that behavioural effects may diverge from effects on *mental models*.

### Challenges in Capturing Mental Models

Accurately capturing *mental models* presents a significant challenge in research, particularly when studying complex systems such as ecodriving. A primary difficulty lies in the deeply embedded nature of this knowledge, which often resists easy verbalisation. Endsley (2000, p. 4) highlights that “simple articulation of a *mental model* of some system at any level of detail has proven to be unusually difficult. This is because such knowledge is deeply embedded, making it very difficult to verbalise.” Empirical findings support this view, showing that experts’ knowledge and behavioural control frequently operate at a level of automaticity, where actions are retrieved directly from memory without deliberate reflection (e.g., Klein et al., 1986; Klein & Calderwood, 1991; Logan, 1988, 2018). In this regard, multiple levels of action regulation present additional complexity, varying from conscious reflection to automatic execution (Frese & Zapf, 1994; Rasmussen, 1983). This implies a methodological challenge: individuals may operate on different regulatory levels depending on their experience, skills, and situational demands. Consequently, when assessing drivers’ ecodriving knowledge, the question arises to what extent their *mental models* are verbally accessible—particularly in the case of experienced drivers whose behaviour may be largely automatised.

Nevertheless, several methods have been developed to infer *mental models*, including questioning techniques, interviews, cognitive mapping, card sorting, cognitive task analysis, and performance (Harper & Dorton, 2019; Jones et al., 2011; Rowe & Cooke, 1995). In the domain of ecodriving, think-aloud protocols, interviews and self-reported measures have been used to gain insight into drivers’ knowledge (Arend et al., 2019; Arend & Franke, 2017; Franke et al., 2016; Lai, 2015; Neumann & Krems, 2015; Pampel et al., 2015; Sureth et al., 2019; Wu et al., 2017). In addition, knowledge was also implicitly operationalised under the assumption that higher consumption estimation certainty reflects greater subjective knowledge (Neumann & Krems, 2016). Pampel et al. (2015) emphasise the value of think-aloud protocols but also note limitations, such as incompleteness and inconsistencies between verbalisations and actual behaviour. Nevertheless, behavioural data is used in prior research to assess whether the drivers’ *mental models* are present, correct and activated.

Despite the methodological difficulties, *mental models* are crucial in human factors research (Endsley, 2000). A key question is how different operationalisation perspectives on ecodriving *mental models* can be meaningfully derived despite these methodological challenges. The following three approaches—assessing verbalisable knowledge, measuring perceived

knowledge, and evaluating perceived support of the *mental model*—offer theoretically grounded and empirically plausible ways to make ecodriving mental representations accessible.

In line with the TCI model, accessible actual knowledge and perceived knowledge shape the driver's perceived capability, which serves as a central input to the comparator (see Figure 1). Operationalising the verbalisable component of a *mental model* as a measurable proxy for accessible knowledge enables a more precise examination of how this knowledge dimension interacts with the feedback approach. Identifying verbalisable false beliefs remains particularly informative, as it reveals how different feedback approaches may foster the development of either accurate or erroneous assumptions. Here, it can be assumed that ecodriving knowledge is more accessible and verbalisable than more automated forms of driving knowledge, as ecodriving is typically regulated more consciously and effortfully than everyday driving (Pampel et al., 2018). This aligns with theoretical assumptions that less experience and the presence of errors shift action regulation from automatic to conscious, knowledge-based processing (Frese & Zapf, 1994; Rasmussen, 1983).

Moreover, perceived ecodriving knowledge provides a foundation for understanding the cognitive and motivational prerequisites for effective behaviour change. Even when actual *mental models* are challenging to assess comprehensively, individuals who perceive themselves as competent are more likely to engage in metacognitive strategies, persist longer, and perform better (Pelikan et al., 2021; Yeung et al., 2014). Perceived competence has also been shown to mediate the effect of goals on learning strategies and performance, underlining its central role in mobilising self-regulatory behaviour (E. Cho et al., 2018; Y. Cho et al., 2011; Elliott & Dweck, 1988; Kaplan & Midgley, 1997; Leondari & Gialamas, 2002). Additionally, findings also indicate that perceived capacity belongs to the strongest predictors of behavioural intention (McEachan et al., 2016).

At the same time, the perceived support of the *mental model* represents a distinct but complementary construct: it reflects the subjective quality of comprehension-based guidance. As such, it is not a user trait but a perceived characteristic of the system–user interaction. This construct becomes particularly relevant in the context of rather consciously regulated behaviours such as ecodriving, where drivers rely on system feedback to foster understanding, support decision-making, and enable adaptive behavioural regulation.

### 2.3. Systematic Literature Search on Ecodriving Research

Building on the role of *mental models* in successfully regulating ecodriving behaviour, the following section systematically examines how previous research on ecodriving feedback has addressed key aspects relevant to the development and evaluation of such interventions in general, including energy or fuel consumption reduction effects, powertrain types, forms and content of feedback approaches, study methodologies, as well as other relevant outcome measures (i.e., understanding of energy-efficient driving, quality of action regulation).

A systematic literature search covering the period from 2018 to March 2025 was conducted to reflect the current state of the literature on ecodriving. This search extends the hand-searched sources included in the dissertation's studies as well as existing reviews and meta-analyses.

#### Background

Several literature reviews published in the past years have addressed different facets of ecodriving, particularly on the effectiveness of training, feedback, and persuasive design strategies.

Kurani et al. (2015) conducted a comprehensive review of 40 empirical studies on operational ecodriving behaviours to inform policymakers about the effectiveness of various intervention strategies. The review emphasises that in-vehicle feedback emerged as the most commonly used approach to promote ecodriving and was generally found to be more effective than training alone. However, the authors critically underline that most studies focused on a single strategy without comparing different feedback approaches. A key concern raised by the review is the limited consideration of (behavioural) theory in designing ecodriving feedback approaches or the interaction between driver characteristics, specific behaviours, and contextual factors. As a result, findings are hard to generalise, and there is little guidance on which interventions are most effective in which contexts. The studies' effects on fuel consumption vary between no effect and up to 24.0%, depending on methodological factors (e.g., field or lab) and the type of approach used (e.g., feedback system, instruction, coaching). The authors argue that the full potential of ecodriving can only be realised through an equally sophisticated understanding of human behaviour. They call for future research that employs meta-analyses and theory-driven empirical studies to better understand which interventions work, for which behaviours, and under what conditions.

Dahlinger and Wortmann (2016) reviewed 25 studies based on the assumption that feedback is generally more effective than training or education. They analysed feedback studies regarding sample size, observation duration, environment, type and frequency of feedback, and reported

fuel savings. Their results showed that feedback often led to more energy-efficient driving, with effects ranging from no effect to 32.0% fuel reduction. They attributed this variation largely to methodological inconsistencies. They criticised the overall low methodological quality of the literature, pointing to issues such as small sample sizes, short observation periods, and insufficiently described procedures.

Allison and Stanton (2019) provided a narrative review on ecodriving, emphasising the importance of long-term behavioural maintenance. They highlighted the potential of ecodriving to reduce fuel consumption and emissions and discussed key insights on ecodriving knowledge, training, and feedback across various modalities. The authors concluded that although ecodriving offers economic and environmental benefits, drivers need ongoing feedback to maintain these behaviours over time, and that both individual motivations (e.g., financial, environmental) and real-time performance feedback are crucial.

Sanguinetti et al. (2020) conducted a statistical meta-analysis of ecodriving feedback interventions, including 17 studies and 23 effect sizes. They estimated an average improvement in fuel economy of 6.6% and found that feedback was more effective when it included instantaneous and accumulated performance information. They also noted common limitations across the literature, particularly the small sample sizes. The authors recommended that feedback systems include high and low granularity information, comparative standards, and gameful design elements.

Paraschivoiu et al. (2019) and Stephens (2022) took a different perspective and reviewed previous studies by referring to persuasive system design. Paraschivoiu et al. (2019) analysed ecodriving systems based on levels of decision-making in persuasive design, such as intent, cues, principles, and design choices. Stephens (2022) focused on the theoretical foundations and specific persuasive features used in systems, including leaderboards, challenges, rewards, and feedback elements such as speed, braking, RPM, coasting, fuel or energy use, and CO<sub>2</sub> emissions.

In addition to reviews and meta-analyses, several individual studies also provide an overview of the effects of ecodriving and ecodriving interventions on fuel consumption and emissions reported in the literature. For example, Husnjak et al. (2015) summarise fuel savings due to ecodriving ranging from 5.0% to 32.0% based on various sources. Similarly, González et al. (2021) provide a tabular summary of the findings from their literature review, focusing on studies involving training, real-time feedback, or reward systems, and report a decrease in fuel consumption ranging from no effect up to 15.7%.

### Method

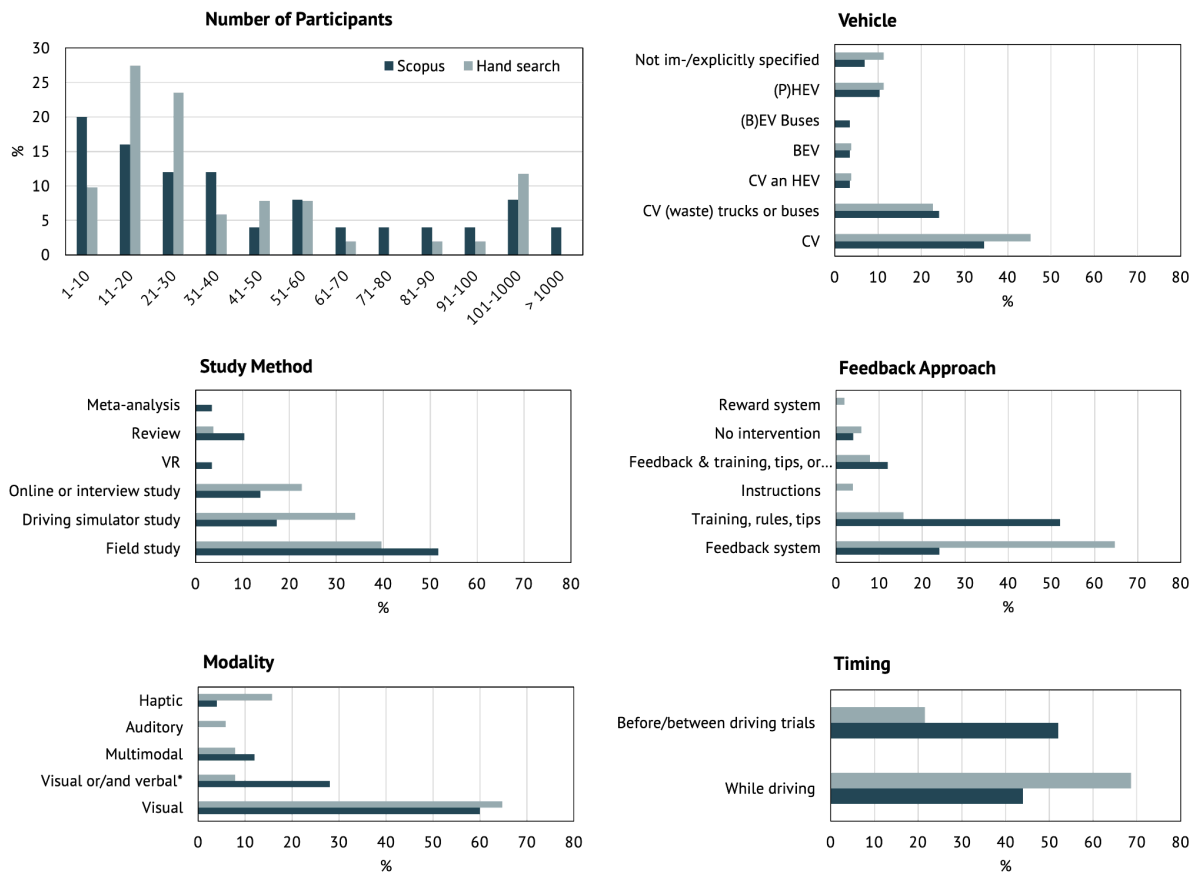
The literature search was conducted using the Scopus database to identify recent publications addressing ecodriving interventions and strategies that support ecodriving. The search was limited to English-language publications. The following Boolean search string was used to query titles, abstracts, and keywords: ("interface\*" OR "display\*" OR "HMI\*" OR "tip\*" OR "training" OR "rule\*" OR "feedback") AND (("eco driving") OR ("ecodriving") OR ("eco-driving") OR "energy-efficient driv\*"). To ensure the relevance of the results, several areas were excluded, including medicine, veterinary science, pharmacology, chemistry, biochemistry, arts and humanities, agriculture, chemical engineering, earth sciences, materials science, and physics. Publications primarily focused on reinforcement learning, deep learning, or autonomous vehicles were already defined as exclusion criteria. The initial search yielded 113 results. Following an initial abstract screening, 62 articles were excluded due to a lack of relevance to ecodriving behaviour or a purely technical focus. After a second detailed screening, a further 13 articles were excluded due to their primary focus on algorithm development, data logging modules, connected vehicles, or deep learning. Even though some of them included data collection, it was conducted for validation purposes and not for investigating effects on human behaviour. A further nine articles were excluded due to a lack of access. Finally, 29 articles were considered for further review. As a complementary hand search, 53 articles from the targeted literature searches for the dissertation studies were added (primarily published until 2018). The final sets of included articles ( $N = 29/53$ ) were analysed concerning several key dimensions relevant to the research focus. Specifically, each publication was coded, where information was available, according to the type of vehicle powertrain studied (i.e., ICEV, BEV, HEV) and the research method used (e.g., driving simulator study, field study, online or interview study). In addition, the type of feedback approach was categorised into training programs, tips, ecodriving feedback systems (e.g., displays, auditory signals), or combinations of these. The feedback approach's timing (e.g., before or between driving trials, while driving) and the modality (e.g., visual, multimodal) were coded. Lastly, the reported intervention effects are briefly reviewed, emphasising consumption outcomes and the assessment of knowledge or usability.

### Results

Figure 2 visualises the coding results and separately presents the supplementary hand search, as this search cannot be described as systematic or comprehensive.

Figure 2

Overview of the Literature Search



Note. \*Training format not clearly specified. Percentages of modality, timing and feedback approach are calculated relative to the number of studies, excluding meta-analyses and reviews. Since not all studies included interventions, the percentages for feedback approach, modality, and timing do not always sum to 100%.

### Sample Sizes

Most of the identified studies rely on small sample sizes, in line with previous critical findings (e.g., Dahlinger & Wortmann, 2016; Sanguinetti et al., 2020). Specifically, 48.0% of the studies from the systematic literature search and 60.8% identified through the hand search used samples of  $\leq 30$  participants. Some authors underline that small sample sizes of 20–30 are typical for driving simulator studies because they are resource-intensive (Y. Wu et al., 2017). Nevertheless, this raises concerns about the generalisability and statistical power of many reported findings.

### *Type of Vehicle Powertrain*

The majority of the existing research still focuses on ICEVs. Only around 17.2% of the studies from the systematic literature search and 15.1% from the hand search exclusively and explicitly examine the effects of ecodriving interventions in BEVs or HEVs. While it can be generally assumed that the core principles of interaction with ecodriving feedback approaches are comparable, the magnitude of effects on energy consumption and the specific requirements for different driving strategies in EVs warrant differentiated consideration. This highlights a critical gap in the literature, particularly given the increasing relevance of BEVs.

### *Study Method*

A trend toward field studies can be observed, particularly in more recent studies from the systematic literature search (51.7%). At the same time, depending on their validity level, driving simulator studies (17.2%) can offer a suitable environment for systematically investigating driver behaviour and the effects of ecodriving interventions. Their key advantages include high experimental control, replicability, and low risks. The hand search reveals a somewhat different distribution: field studies account for 39.6%, while driving simulator studies represent a larger share at 34.0%. Notably, the proportion of online or interview-based studies is considerably higher in the hand search (22.6%) compared to the systematic literature search (13.8%). Reviews and meta-analyses comprise only a small portion of both datasets (3.5%–13.3%), and virtual reality studies are relatively rare (3.5% in the systematic literature review).

### *Feedback Approach*

Interestingly, although some authors emphasise that ecodriving feedback is essential for learning and maintaining ecodriving behaviour in the long term and more effective than training interventions, the systematic literature review revealed a strong emphasis on training or tip-based interventions (52.0%) compared to feedback systems (24.0%) or combined approaches (12.0%).

In contrast, the hand search, comprising primarily older publications, focused more heavily on investigating feedback systems (64.7%) than on training or tip interventions (15.7%), combined approaches (7.8%), instructions (3.9%), or reward systems (2.0%). This aligns with the findings of Kurani et al. (2015).

### *Modality and Form of Visual Feedback*

Consistent with older reviews, the literature focuses on visual feedback systems (60.0–64.7%). Therefore, the advantages of visual feedback and its implementation in previous studies are

described in more detail. Various advantages of visual feedback have already been discussed in the literature. Primarily, it can be more detailed than haptic or auditory feedback. More precisely, more possibilities exist to enrich the information through symbols and colours and their associations. Besides, visual information can be provided simultaneously, and it is therefore possible to give particular information faster than sequentially presented information in other modalities (auditory, haptic). Based on these benefits, different types of visual feedback were examined, like concrete vs. abstract or symbolic, colour-coded and numerical values, as well as classic consumption or battery-related visualisations like diagrams, gauges or energy flows (Brouwer et al., 2015; Dahlinger, Tiefenbeck, et al., 2018; Graving et al., 2010; Lundström & Bogdan, 2014; Meschtscherjakov et al., 2009; Schwarze et al., 2019; Stillwater & Kurani, 2013, 2014; Tulusan et al., 2012). Additional examples include symbolic and colour-coded visual warnings (Chang et al., 2021), eco-scores and colour- and size-coded symbols (Colley et al., 2022), and colour-coded retrospectives of the drive (McConky et al., 2018). The interfaces included elements such as driving metrics (e.g., consumption values, speed, gear selection) or behavioural feedback on aggressiveness, speeding, idling time, excess RPM, appropriate braking and acceleration, or optimal use of the accelerator pedal (Brouwer et al., 2015; Dahlinger, Tiefenbeck, et al., 2018; Graving et al., 2010; Hibberd et al., 2015; Jamson et al., 2015; Rolim & Baptista, 2018; Stillwater & Kurani, 2013, 2014; Tulusan et al., 2012; van der Voort et al., 2001). In some approaches, textual feedback in the form of simple instructions, improvement information, or hints such as gear selection or acceleration strength is visually offered (e.g., Andrieu & Saint Pierre, 2012; Chang et al., 2021; Meschtscherjakov et al., 2009; Rolim & Baptista, 2018; Tulusan et al., 2012; van der Voort et al., 2001; Zhao et al., 2015). One study presented the target behaviour as concrete feedback of current vs. target speed within the tachometer (Allison et al., 2019). Some studies also include comparison information like leaderboards (McConky et al., 2018), average values of other drivers (Yamin et al., 2021), or driving ranking (Ayyildiz et al., 2017).

It has to be mentioned that visual or verbal training formats and their content are often described only superficially (e.g., Ayyildiz et al., 2017; Günther et al., 2019; Savković, Gladović, et al., 2019; Savković, Miličić, et al., 2019; Savković et al., 2020; Y. Wu et al., 2018; Yamin et al., 2021; Zarkadoula et al., 2007), which prevents an elaborated and comparable analysis of which specific elements are effective. Studies that primarily focus on communicating tips or rules (e.g., Beloufa et al., 2019; Beusen et al., 2009; Rouzikhah et al., 2013; Sureth et al., 2019) and a few training studies (e.g., af Wåhlberg, 2007) tend to be a little more precise in this regard. However, other descriptions are sometimes limited to general statements and partial examples (e.g., Daun et al., 2013; van der Voort et al., 2001). In some cases, different training formats are combined but not systematically differentiated. For example, Jeffreys et al. (2018) reported general effects of an ecodriving training but did not provide detailed information on its

components. The intervention encompassed five distinct training interventions—including an online learning module, a brochure, a classroom lesson, a combination of online tools with a driving lesson, and blended formats involving classroom lessons, workshops, and online tools—without further specification or differentiated analysis. As a result, it remains unclear which specific elements contributed to changes in drivers' knowledge or behaviour.

### *Timing*

The systematic literature search revealed a relatively balanced distribution between interventions delivered before or between drives (52.0%) and those during driving, such as real-time feedback (44.0%). In contrast, older studies considered through the hand search show a stronger emphasis on interventions while driving (68.6%). Some studies also combined dynamic feedback during driving (e.g., voice prompts, real-time CO<sub>2</sub> emissions) with static feedback after driving, like fuel consumption rank, fuel saving potential, and static ecodriving rules (Zhao et al., 2015).

### *Effects on Performance, User Experience, and Knowledge*

In the systematic literature search, fuel consumption reductions in ICEVs following training or tip-based interventions ranged from 2.4% to 17.6% (García et al., 2018; Jeffreys et al., 2018; Poolkrajang, 2024; Savković, Gladović, et al., 2019; Savković, Miličić, et al., 2019; Yamin et al., 2021). One study even reported a reduction of up to 27.8%, including truck drivers who received intensive training as part of their employment (Arroyo-López et al., 2022). Studies focusing solely on feedback systems reported reductions in fuel consumption for ICEVs ranging from 2.0% to 8.5% (Allison et al., 2019; Dahlinger, Tiefenbeck, et al., 2018).

In the hand search, fuel consumption reductions in ICEVs with a focus on feedback systems ranged from no effect up to 18.4% (Adell et al., 2008; Azzi et al., 2011; Dahlinger, Wortmann, et al., 2018; Dib et al., 2014; González et al., 2021; Larsson & Ericsson, 2009; Martin et al., 2013; Nouveliere et al., 2012; Staubach et al., 2014; Vagg et al., 2013). For studies focusing on tips, instructions, and training, reported reductions ranged from no effect up to 16.9% (Andrieu & Saint Pierre, 2012; Ayyildiz et al., 2017; Beusen et al., 2009; Daun et al., 2013; Miotti et al., 2021; Pampel et al., 2015, 2017, 2018; Pinchasik et al., 2021; Sullman et al., 2015). It must be mentioned that not all studies include an inferential statistical analysis of consumption (e.g., Dib et al., 2014; Martin et al., 2013; Nouveliere et al., 2012; Zarkadoula et al., 2007).

Previous ecodriving research has incorporated a variety of behavioural measures beyond fuel or energy consumption to assess driving behaviour more comprehensively. These include coasting distance (Beusen et al., 2009), percentage of time spent in heavy acceleration or deceleration

phases (Beusen et al., 2009), and the mean or standard deviation of deceleration and acceleration values (Birrell et al., 2014; Martin et al., 2013; Y. Wu et al., 2017). Additional indicators comprised pedal use patterns or driving errors (Birrell et al., 2014; Hibberd et al., 2015; Jamson et al., 2015), mean or median speed (Daun et al., 2013; Dib et al., 2014; Martin et al., 2013; Savković, Gladović, et al., 2019; Stillwater & Kurani, 2014; Sullman et al., 2015; Y. Wu et al., 2017), frequency of (un)desired events such as harsh braking or sudden acceleration (Rolim et al., 2014; Savković, Gladović, et al., 2019; Sullman et al., 2015; Y. Wu et al., 2017), as well as pedal usage time or distance (Savković, Gladović, et al., 2019). However, some of these studies did not report inferential statistical analyses of behavioural performance (e.g., Dib et al., 2014; Martin et al., 2013; Rolim et al., 2014), and some found no effects or effects limited to specific metrics or situations (e.g., Hibberd et al., 2015; Savković, Gladović, et al., 2019; Sullman et al., 2015).

Besides behavioural and energy-related performance, a few studies included subjective evaluations of the feedback approaches, such as satisfaction (Lee et al., 2011), attitudes toward the system (Fors et al., 2015), user acceptance (Meschtscherjakov et al., 2009)—sometimes measured with the Van der Laan Acceptance Scale (Rakauskas et al., 2010; Staubach et al., 2014; Van Der Laan et al., 1997)—as well as system usability (Allison et al., 2019; Colley et al., 2022; Young et al., 2009). Although the System Usability Scale (SUS; Brooke, 1996) is an established and validated scale (Lewis & Sauro, 2018; Sauro & Lewis, 2016), it seems not perfectly-suited for evaluating ecodriving feedback systems as it was designed to assess general system usability across a wide range of technologies, rather task-specific, real-time systems embedded in complex action regulation contexts. While the SUS focuses on broad aspects such as ease of use, complexity, and confidence, it does not capture critical dimensions of how feedback supports distinct information processing stages during the adaptive control of behaviour. Without a detailed examination of these specific action regulation aspects, it can not be determined why and how specific feedback approaches are perceived as supportive from a cognitive perspective. Consequently, the SUS lacks the sensitivity to address the cognitive and dynamic processing requirements essential for effective ecodriving feedback. In addition to conceptual limitations, results regarding the SUS are not always reported (Allison et al., 2019). Moreover, other studies utilised non-standardised, self-developed measures. For example, Poolkrajang (2024) used items like “The content is appropriate for the trainees”, while Rolim and Baptista (2018) developed items assessing perceived contribution to behavioural change and satisfaction. Brouwer et al. (2015) used seven items (e.g., “In general I believe the system is useful” or “I deliberately drove more ecofriendly”) and reported average scores on usefulness per item. Staubach et al. (2014) developed 26 items to assess the perceived ease of use, perceived usefulness, and behavioural intention to use (e.g., “Using the system helps me to save fuel” or “My interaction with the system was clear and understandable”). Neumann and Krems

(2016) assessed usability by two items concerning display reliability and perceived helpfulness. However, these approaches are often even more generic than the SUS and sometimes lack optimal item construction. The items of the Van der Laan Acceptance Scale (e.g., useful vs. useless or effective vs. annoying) are also very global, do not differentiate between information processing stages, and convergent validity has rarely been examined (Zoellick et al., 2021).

Mental representations are considered central to effective and efficient action regulation. However, as described in more detail in section 2.2, only a few studies employed methods to assess and examine participants' knowledge (Arend et al., 2019; Arend & Franke, 2017; Franke et al., 2016; Lai, 2015; Neumann & Krems, 2016; Pampel et al., 2015; Sureth et al., 2019; Y. Wu et al., 2017) or focus on the activation of and sustainable behavioural impact of *mental models* (Pampel et al., 2017, 2018).

### Summary

A review of existing literature, older reviews, and a meta-analysis reveals that various ecodriving feedback approaches can potentially promote more energy-efficient driving behaviours. However, across studies, there is a notable lack of systematic differentiation between types of feedback approaches and their underlying cognitive mechanisms. Feedback is rarely conceptualised as an informational intervention to foster deeper understanding or anticipatory regulation. Most studies focus on (immediate) behavioural outcomes (e.g., accelerating, speeding) without sufficiently addressing the cognitive information processing stages involved. Furthermore, subjective driver perceptions—such as the perceived support of effective and efficient action regulation or perceived energy-efficiency of driving strategies derived from the respective feedback approach—are rarely assessed, despite their relevance for long-term integration and acceptance in everyday driving. A further gap lies in the limited attention given to BEVs. While most studies focus on ICEVs, BEVs remain underrepresented, despite their unique energy management characteristics and additional opportunities for targeted feedback (e.g., regenerative braking). As previously noted in reviews by Dahlinger and Wortmann (2016) and Sanguinetti et al. (2020), persistent methodological limitations, including small sample sizes, continue to undermine the reliability and generalisability of findings. Furthermore, many studies lack a solid theoretical foundation, often omitting reference to established models of learning, cognition, or behavioural change, with some exceptions (e.g., Dahlinger, Wortmann, et al., 2018; Stillwater & Kurani, 2012; Sureth et al., 2019). Feedback strategies are frequently developed without systematic derivation from scientific principles or psychological theories. This absence of conceptual grounding limits both explanatory depth and the broader contribution to engineering psychology.

Accordingly, there is a strong need for more theory-informed and differentiated investigations of feedback approaches, particularly in the context of BEV, that explicitly address different stages of information processing and *mental model* formation, support both objective action regulation and subjective experience, and are grounded in robust and systematic methodology.

### **2.4. Automation in Ecodriving Feedback Approaches**

How ecodriving feedback is designed and integrated into driver-vehicle interfaces is deeply intertwined with broader questions of automation, human oversight, and shared control. To examine and distinguish between different feedback approaches, it is essential to consider how drivers engage with varying degrees of automation. The following section outlines a conceptual framework for human interaction with automation, providing a foundation for examining how differentially automated ecodriving feedback approaches can, in psychologically grounded ways, support action regulation.

Parasuraman, Sheridan, and Wickens (2000) developed a framework for understanding the types and levels of human interaction with automation, aiming to guide decisions on which functions to automate and to what extent. Their model distinguishes four functional stages of human information processing where automation can be applied: (1) information acquisition, (2) information analysis, (2) decision selection, and (4) action implementation. Within each stage, automation can vary across a continuum of levels, from fully manual to fully automated, reflecting increasing system involvement and decreasing driver control. Regarding control-theoretic models of behaviour (Carver et al., 2015; Carver & Scheier, 1982, 1998, 2000; Powers, 1973), automation may be applied to the input function, the comparator, and the output function. The paper's central argument is that automation does not merely replace human activity but transforms it, often introducing new and sometimes unforeseen demands.

For instance, the automation of information acquisition encompasses activities such as sensing and registering data, and it can range from merely displaying raw values to sophisticated information filtering. At a low level, this may involve presenting the driver with raw, real-time energy consumption values without further processing. A moderate level might include highlighting high-consumption periods visually to draw attention to inefficient behaviour. At a high level, the system may selectively present information only when certain thresholds are exceeded, such as triggering ecodriving feedback exclusively during instances of particularly inefficient acceleration or braking.

Similarly, the automation of information analysis refers to cognitive functions like manipulating and integrating data before decision-making. At a low level, the system may apply basic

algorithms to extrapolate patterns over time, such as computing average energy consumption over the past ten kilometres. A moderate level involves integrating multiple variables into a single performance metric, for instance, by calculating an ecoscore that reflects acceleration behaviour, braking intensity, and speed variability. At a high level, the system may perform context-sensitive analyses, such as identifying that inefficient driving predominantly occurs during stop-and-go traffic and generating personalised feedback accordingly.

Decision and action selection automation focuses on how recommendations or choices are presented to the driver. At a lower level, the system may suggest gear shift points, leaving interpretation and decision to the driver. A moderate level might include recommending specific driving behaviours based on contextual factors, such as suggesting neutral gliding in anticipation of traffic lights and effects on consumption. At the highest level, the system could propose an optimal speed trajectory for a given road segment, factoring in gradient, traffic, and energy efficiency goals, influencing the driver's behaviour more directly.

Finally, automation of action implementation refers to the degree to which a system carries out actions that would otherwise require input from the driver. At a low level, the driver still executes most actions based on system feedback. At a moderate level, systems such as eco-adaptive cruise control automatically adjust vehicle speed for optimal efficiency, though the driver can override the system at any time. At a high level, the system may assume complete control over driving to minimise energy consumption without requiring driver intervention. Despite continued progress in vehicle automation, numerous challenges still impede its near-term implementation (e.g., Kosuru & Venkitaraman, 2023). Thus, manual action implementation by drivers remains highly relevant today and is expected to continue playing a critical role in the coming years, also in the context of partially automated driver assistance systems and requirements to take over control when needed.

Parasuraman et al. (2000) underline that while automation can enhance system performance, it also entails trade-offs. Higher levels of automation may reduce workload, but they also risk decreasing *situation awareness*, promoting complacency, and contributing to skill degradation—phenomena often associated with the “out-of-the-loop” problem (Wickens, 1995). Onnasch et al. (2014) conducted a meta-analysis of 18 experimental studies to investigate how different degrees of automation affect human-system interaction outcomes. Their findings demonstrate that while increasing automation can improve routine performance and reduce workload, it can simultaneously diminish *situation awareness* and manual skills. Crucially, the analysis identified a “critical boundary” at the transition point between information analysis automation and automation of decision selection. Crossing this boundary appears to increase the likelihood of adverse outcomes significantly. The authors note that current approaches do not allow for a precise quantification of the degrees of automation on ratio or interval scales,

nor do they resolve trade-offs across automation stages. They call for further controlled, psychophysically grounded research to enable the development of more differentiated and actionable metrics (Onnasch et al., 2014). For example, one study with higher automated speed recommendations demonstrated an 8.5% reduction in fuel use (Allison et al., 2019). Still, the differentiated cognitive effects compared to lower automated feedback approaches remain unclear, as the comparison was only an unassisted condition. Usability and workload results were not reported, and measures related to *mental models* or *situational models* were not examined.

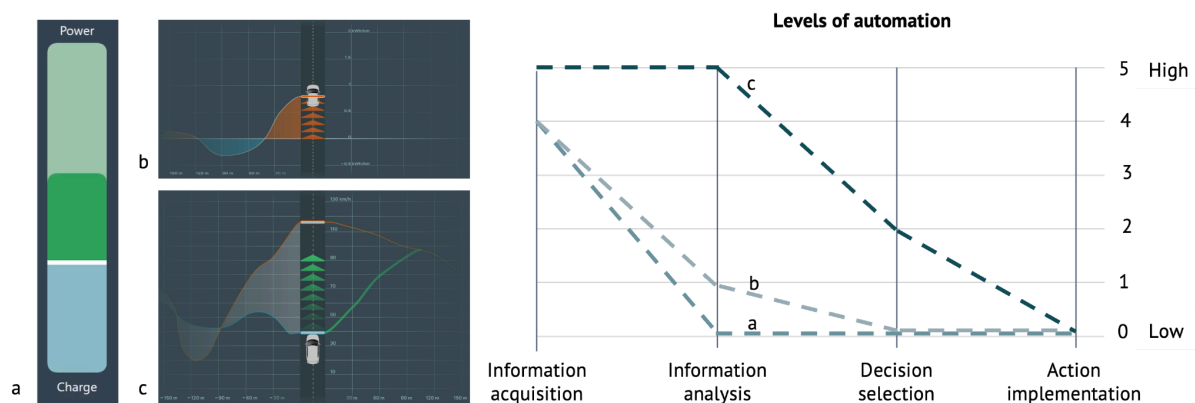
Ruscio et al. (2024) offer a critique and conceptual extension of existing automation frameworks, particularly addressing limitations in model by Parasuraman et al. (2000). They argue that while mapping functional capabilities and allocating tasks between humans and automation provides a crucial foundation for interface design, current one-dimensional frameworks struggle to deal with new systems and precisely categorise levels of automation. Besides, the authors criticise the limited support for identifying outcomes of human-automation interactions, not distinguishing between skill-based, rule-based, and knowledge-based behaviour, and inadequate means for addressing dynamic task allocation among other aspects. To address some of these challenges, Ruscio et al. (2024) propose the *General Automation Level Allocation* (GALA) framework with a taxonomy of six levels of automation, ranging from 0 (no or only low-tech artefact support) to 5 (fully automated function completely decoupled from human). A decision tree is provided to determine the levels of automation according to GALA, and it leads to a slightly different assignment of what constitutes a low, moderate, or high degree of automation compared to the verbal classifications by Parasuraman et al. (2000).

Figure 3 illustrates the application of the GALA framework to three ecodriving feedback approaches: (a) an instant consumption display, (b) a consumption trace display over time, and (c) a display of current and optimal speed. Approach (a) represents a low-level automation approach, providing raw consumption data with minimal processing or guidance. Regarding information acquisition, it filters the represented metric and its unit observable for the driver. It scores low across the other information processing stages, indicating high reliance on the drivers' interpretative and decision-making capabilities. Approach (b) adds colour-coded information (e.g., energy consumed vs. regenerated) and temporal context through the visualisation of a consumption trace, moderately increasing the level of information analysis by allowing drivers to infer trends and relieving the maintenance in the working memory. However, the in-depth information analysis remains with the drivers. Besides, it still lacks decision support or action execution, and thus remains low in those categories. Approach (c) exemplifies a more advanced form of automation. It provides context-sensitive feedback by giving a target value (i.e., optimal speed) based on unobservable information acquisition and analysis, thereby

offering real-time performance guidance. The criteria for filtering and analysing information are not accessible to the driver. There is only one preselected speed recommendation per point in time, and the driver can generate and select a different decision alternative. Thus, this feedback significantly elevates the automation levels in information acquisition and analysis, and moderately in decision selection, although it does not automate action execution.

**Figure 3**

Automation of Ecodriving Feedback Approaches Rated Based on the GALA Framework



*Note.* a: Instant consumption display. b: Instant consumption trace display. c: Display of current and optimal speed.

It is important to note that different GALA ratings may result depending on how “filtering” is defined (i.e., filtering the consumption metric and the unit, or filtering relevant information within the presented variable). If the selection of the consumption metric, unit, and format is interpreted as a filtering process, a score of 4 can be assigned to the consumption displays, since the filter criteria are visible but not modifiable. However, if filtering is interpreted strictly as the selection of relevant information from the displayed variable, a score of only 1 would be appropriate.

Similarly, alternative ratings for decision selection may be justified. While a score of 2 reflects the driver’s ability to reject the system’s speed recommendation in favour of their own, higher scores could be warranted, as the system also makes decisions that are not observable—such as predefined algorithm parameters for balancing time and energy. If such decisions are considered in the rating, a score of 5 may be appropriate (decision not observable, fully decoupled). Moreover, the GALA framework represents only one possible approach for classifying or distinguishing between different feedback approaches. For example, the

## Theoretical Background

framework does not differentiate with regard to other factors that may also influence the effects of feedback, such as the amount of information provided or the quality of the representation.

In sum, the costs and benefits of automation necessitate a careful evaluation of its implications for drivers' information processing when selecting appropriate degrees of automation in ecodriving feedback approaches. While existing frameworks provide a possible classification of automation degrees, there is ultimately no universal optimum. Therefore, empirical evidence regarding behavioural and cognitive outcomes in the ecodriving context should guide the appropriate degree of automation.

### 3. Research Objectives

Building on limitations identified in prior ecodriving research, the present dissertation investigates how different ecodriving feedback approaches can support drivers' information processing within action regulation and foster ecodriving-related knowledge and performance. Previous studies have predominantly focused on ICEVs and have rarely addressed drivers' subjective experience systematically and theory-based, alongside performance outcomes. Although constructs such as acceptance or perceived usefulness are occasionally reported, they are often measured using self-created items and without differentiation across human information processing stages. Moreover, while the formation of adequate *mental models* is considered essential for effective and efficient action regulation (e.g., Baumann & Krems, 2007, 2009; Endsley, 2000; Franke & Krems, 2013; Frese & Zapf, 1994; Zacher & Frese, 2018), these have been considered too little in the ecodriving contexts. Following previous reviews, ecodriving feedback approaches were frequently evaluated against a "no support" baseline, rather than against soundly derived alternatives. Consequently, the potential mechanisms through which specific feedback designs affect information processing, knowledge, and behaviour remain insufficiently understood.

Table 1 outlines the dissertation's ROs and indicates which studies most closely align with each objective. In Figure 1, the ROs are linked with their thematic focus within the adaptive control of ecodriving behaviour.

**Table 1**  
Research Objectives of the Dissertation

	Objective	Studies
RO1	How do different feedback approaches influence users' perception, judgements, and implementation of energy-efficient driving strategies?	1, 2, 3, 4
RO2	To what extent do different feedback approaches support users' understanding of energy-efficient driving?	2, 3, 4
RO3	How do different feedback approaches influence users' subjective quality of action regulation?	2, 3, 4

### **RO1: How Do Different Feedback Approaches Influence Users' Perception, Judgements, and Implementation of Energy-Efficient Driving Strategies?**

A differentiated analysis of users' perceptions, judgements, and action implementation is essential to fully understand the mechanisms underlying ecodriving behaviour. This differentiation is particularly critical because inexperienced drivers face elevated cognitive demands when interpreting and acting upon feedback, often struggling with information overload or misinterpretation. Conversely, experienced drivers confront the challenge of deliberately overriding well-established habitual routines, a process requiring significant cognitive effort and motivation. Feedback approaches may fail to address specific user needs or cognitive constraints without an enhanced understanding of effects on perception, judgments, and action implementation. By explicitly targeting these aspects, researchers and designers can develop more effective, tailored interventions that enhance feedback comprehension and actual behavioural change. This approach not only increases the likelihood of sustained ecodriving adoption but also advances theoretical models of complex action regulation in real-world settings.

Thus, RO1 addresses the lack of theory-driven comparisons between feedback approaches by systematically examining how specific informational designs shape drivers' interpretation and behavioural integration of ecodriving strategies. It helps identify whether standard feedback approaches support accurate perceptions and judgments of energy efficiency (Study 1) as a foundational step. Furthermore, it examines the behavioural implications of further feedback approaches by comparing their effects on energy consumption and behavioural driving metrics (Studies 2–4).

### **RO2: To What Extent Do Different Feedback Approaches Support Users' Understanding of Energy-Efficient Driving?**

Assessing drivers' subjective knowledge and understanding is essential when investigating ecodriving feedback approaches because it fundamentally influences how feedback is filtered, interpreted and integrated into driving behaviour. Initial evidence suggests that individuals with lower perceived or actual capabilities (e.g., due to limited driving experience or domain knowledge) may fall back on automated, habitual driving behaviours that require less cognitive effort. It remains unclear, however, to what extent conventional feedback strategies, such as instantaneous consumption displays, effectively promote ecodriving knowledge and conclusions. Research among HEV drivers, for instance, has revealed substantial knowledge gaps (Franke et al., 2016). Importantly, assessing perceived knowledge is central because drivers' beliefs about their understanding and, thus, perceived capabilities (Fuller, 2005, 2011)

directly affect their motivation to engage with feedback and apply ecodriving strategies. Even accurate knowledge may remain unused if individuals do not perceive themselves as knowledgeable, while overconfidence can lead to disregarding feedback. Thus, measuring subjective ecodriving knowledge provides crucial insight into the cognitive factors that determine whether feedback translates into actual behaviour change. Measuring perceived knowledge enables the design of feedback systems that are clear, comprehensible, and actionable, thereby enhancing driver acceptance and promoting sustainable behaviour change.

Thus, RO2 responds to the limited attention paid to BEV ecodriving knowledge in previous research by assessing how feedback influences the development of *mental models* and conceptual understanding. It contributes to examining the gaps and accuracy of ecodriving knowledge depending on the ecodriving feedback approach (Study 2), as well as the perceived ecodriving knowledge (Studies 3–4).

### **RO3: How Do Different Feedback Approaches Influence Users' Subjective Quality of Action Regulation?**

Evaluating the subjective quality of action regulation is essential when assessing ecodriving feedback approaches, as it indicates how well users believe they can control and adapt their behaviour based on system feedback. While an ecodriving display might objectively promote energy-efficient driving, if drivers experience it as confusing or overwhelming, sustained adoption and behaviour change are unlikely. Measuring subjective action regulation quality provides insights into drivers' perceived usability and cognitive support, enabling the design of feedback systems that are not only functionally effective but also psychologically supportive. Therefore, integrating subjective evaluations bridges the gap between objective performance and user experience, which is essential for fostering lasting improvements in ecodriving behaviour.

Thus, RO3 addresses the underrepresentation of drivers' subjective experience in ecodriving studies by evaluating what uncertainties exist due to a lack of knowledge (Study 2), how feedback affects perceived support of effective, efficient, and confident action regulation (Studies 3–4) and the perceived support of the *mental model* (Studies 3–4). It expands the focus beyond performance and knowledge measures to explore how different feedback approaches shape drivers' certainty and perceived support across different information processing stages.

## 4. Overview of the Studies

This section summarises the central findings of the four empirical studies included in this dissertation. It highlights the specific contribution of each study to the overarching ROs (see Table 1) and details the individual contributions of involved researchers or co-authors.

As a key preparatory work for Studies 3 and 4, a co-authored publication by Sureth et al. (2019) is integrated into the theoretical background of the dissertation and its studies. However, it is not considered one of the core empirical studies of this dissertation.

### 4.1. Study 1: Biased Energy Efficiency Perception

Moll, V. E., & Franke, T. (2021). Biased energy efficiency perception based on instantaneous consumption displays – Indication for heuristic energy information processing. *Applied Ergonomics*, 94, 103399. <https://doi.org/10.1016/j.apergo.2021.103399>

#### Summary of the Empirical Research

The first study (Moll & Franke, 2021) was published in *Applied Ergonomics* and received the second rank in the *HFES Europe Early Career Award 2020*. The study developed and applied a controlled experimental paradigm to investigate how drivers perceive energy efficiency based on dynamic consumption profiles over time, such as those shown in instantaneous consumption displays (ICDs). The method isolates perceptual variables that shape efficiency judgments by systematically manipulating key visual characteristics—specifically, the height and duration of consumption peaks. This approach enables a precise examination of the cognitive mechanisms underlying users' judgements of energy efficiency.

The results showed that drivers tend to overestimate average energy consumption, particularly when confronted with brief and high peaks. This pattern revealed a systematic reliance on perceptual salience over temporal integration. It suggested that ICDs may unintentionally foster biased or misleading interpretations of energy use, despite being designed to promote energy awareness. The study further identified significant interindividual differences in the susceptibility to these biases: while domain-specific knowledge and affinity for technology interaction (ATI; Franke, Attig, et al., 2019) attenuated perceptual biases, prior experience with ICDs had no mitigating effect. This indicated that mere familiarity with displays is insufficient for accurate interpretation and that individual user characteristics play a central role in feedback processing.

Besides, the findings provided critical insights into the cognitive construction of energy-related mental representations based on visual cues (i.e., snapshots of a dynamic process) and how these representations may systematically deviate from physical reality. They demonstrated that visual feedback formats like ICDs can systematically bias information acquisition and judgement formation, undermining their intended function to support ecodriving. These results challenge the assumption that real-time feedback facilitates learning energy-efficient behaviour and underscore the importance of aligning display design with cognitive processing strategies.

### **Contribution to the ROs**

This study makes key methodological contributions to the dissertation. Most notably, it directly addresses **RO1** by introducing and validating a novel, highly controlled experimental paradigm for assessing how drivers perceive and evaluate energy efficiency based on dynamic trajectories in ICDs. The paradigm allows for the systematic variation of visual characteristics (i.e., peak height and duration), thereby isolating perceptual mechanisms that shape efficiency judgements. Additionally, the study indirectly informs **RO2** by providing empirical evidence on the limitations of standard ecodriving feedback formats in supporting accurate system understanding. Participants failed to accurately judge energy use, suggesting that ICDs do not sufficiently support learning-by-doing or causal reasoning about vehicle consumption. The experimental findings highlight the difficulty of acquiring meaningful system-level knowledge through typical real-time consumption feedback.

Finally, the study extends **RO1** by identifying and quantifying interindividual moderators—specifically, domain-specific knowledge and ATI—as critical factors influencing how dynamic feedback is cognitively processed. These insights inform the design of adaptive or personalised feedback systems that account for user characteristics, thereby improving the interpretability and utility of energy-related driver information.

### **Author Contribution**

I contributed by developing the research idea and conceptualising the study design, materials, and analytical approach. I created the experimental design, prepared the questionnaires, and conducted the formal data analysis and visualisation. I wrote the manuscript under the supervision and critical review provided by Thomas Franke. Please note that Matthias Arend and Tina Petersen contributed to this research as student research assistants, although they are not listed as co-authors. They supported literature research and data analysis.

**CRedit statement:** **Vivien Moll:** Conceptualisation; Data Curation; Formal Analysis; Investigation; Methodology; Visualisation; Writing – Original Draft; Writing – Review & Editing. **Thomas Franke:** Supervision; Writing – Review & Editing.

## 4.2. Study 2: Understanding the Knowledge Gaps in Ecodriving

Moll, V. E., Heidinger, J., Schmees, S., Görges, D., & Franke, T. (2025). Understanding the knowledge gaps in ecodriving: Analysis of knowledge accuracy, uncertainty, and action regulation [Preprint]. *Research Square*. <https://doi.org/10.21203/rs.3.rs-7721857/v1>

### Summary of the Empirical Research

The second empirical study investigated misconceptions and knowledge gaps in ecodriving with BEV across different driving manoeuvre prototypes (e.g., acceleration from standstill, braking to lower speeds), based on a driving simulator experiment with three feedback approaches: a recommendation display of optimal speed, a consumption trace display, and a control group without feedback. Methodologically, the study employed a *Thematic Analysis* (V. Braun & Clarke, 2006) of participants' verbalised ecodriving tips and coded references to control loop components—namely, the input function, comparator, and output function. Besides, tip accuracy (i.e., correctness and precision of tips and their technical explanations) was coded with OpenAI.

Results showed that participants in the recommendation display condition more frequently referenced environmental and vehicle cues (input function), indicating greater attention to information explaining the rationale behind the recommendations. Nevertheless, key concepts such as neutral gliding, conversion efficiency, and aerodynamic effects of high speeds were rarely mentioned or misunderstood. Misconceptions included false beliefs about acceleration intensity, misunderstandings of regenerative braking and coasting (i.e., neutral gliding), and inaccurate assumptions about pedal interaction (e.g., assuming coasting instead of recuperating when releasing both pedals). Many tips were vague, generic, avoidance-based, or lacked system-level reasoning, indicating fragmented *mental models* and limited conceptual integration.

Regarding behavioural outcomes, participants in the consumption trace display condition showed a greater reliance on mechanical braking and less use of regenerative braking. In contrast, participants in the recommendation display condition exhibited lower average speeds during constant driving. However, energy consumption did not significantly differ across groups. While all participants demonstrated comparable low tip accuracy, those in the recommendation display condition reported reduced perceived uncertainty due to a lack of knowledge. Together,

these findings suggest that speed recommendations can shape isolated driving behaviours and reduce perceived uncertainty, but do not reliably improve conceptual understanding or energy efficiency. The results underscore the need for explanatory feedback designs that connect driver actions with system-level reasoning and environmental outcomes to support the development of more adequate *mental models*.

### **Contribution to the ROs**

This study makes foundational contributions to all research objectives. The study directly addresses **RO1** by examining how different feedback approaches affect the implementation of energy-efficient strategies. It identifies selective behavioural adaptations, such as consistent speed regulation in the recommendation display condition and braking differences in the consumption trace condition. These context-dependent effects demonstrate that while ecodriving feedback can shape specific aspects of action regulation, it does not yield generalised performance improvements across manoeuvre types. The study also offers insights into how feedback can influence the verbalisable part of perceived and analysed information (e.g., references to cues from the environment and the vehicle).

Regarding **RO2**, the study provides a profound analysis of participants' verbalisable part of their *mental models* through *Thematic Analysis* as well as quantitative analysis. It reveals that participants struggled to articulate core system-level principles, such as conversion losses while recuperating or aerodynamic drag, even under feedback conditions. These findings emphasise the limitations of current real-time feedback approaches in supporting users' conceptual understanding. The study thereby underscores the necessity for feedback systems that not only prescribe target behaviours but also explain the underlying reasoning to foster deeper causal and structural learning.

By analysing perceived uncertainty due to a lack of knowledge, the study contributes to **RO3** by evaluating how feedback approaches affect drivers' subjective experience of control and confidence based on their knowledge level. While participants in the recommendation display condition report reduced uncertainty, this subjective confidence does not correspond with higher tip accuracy (RO2) or better energy efficiency (RO1). This dissociation highlights a critical tension between perceived and actual competence, suggesting that current feedback may support orientation but not meaningful knowledge acquisition or integration.

### **Author contribution**

I contributed by developing the research idea, conceptualising the study design and the questionnaire scales, the coding script, and the evaluation strategy of the study. I conducted the

quantitative and qualitative data analysis, prepared the visualisations, and wrote the manuscript. Jan Heidinger and Steffen Schmees contributed to this research through pre-processing of driving data and software support. Maged Mortaga implemented the experimental script using OpenAI (OpenAI, n.d.). The underlying and preceding driving simulator study was conceptualised and conducted by Markus Gödker.

Please note that this research was conducted as part of the AMORi project and was only possible through the contribution of the entire AMORi team, including Lukas Bernhardt, Markus Gödker, Jan Heidinger, Steffen Schmees, Elise Banach, Anne Tichy, Leonardt Wagner, Tobias Harms, and others. The technical implementation of the laboratory study setup—including the driving simulator, route sectors, data processing routines, study management system, and display configuration—as well as data collection, was carried out by the AMORi team.

**CRedit statement:** **Vivien Moll:** Conceptualisation; Data Curation; Formal Analysis; Investigation; Methodology; Visualisation; Writing – Original Draft; Writing – Review & Editing. **Jan Heidinger:** Data Curation (pre-processing of driving data); Software. **Steffen Schmees:** Data Curation (pre-processing of driving data); Software. **Maged Mortaga:** Implementing Script (Open-AI). **Tomas Franke:** Funding Acquisition; Resources; Project Administration; Supervision; Writing – Review & Editing.

### 4.3. Study 3: Better Mental Model, Fewer Watt-Hours?

Moll, V. E., Banach, E., Gödker, M., Heidinger, J., Bernhardt, L., & Franke, T. (2025). Better mental model, fewer watt-hours? Effects of ecodriving tips on knowledge, action regulation, and driving performance in battery electric vehicles [Preprint]. *SSRN*. <https://doi.org/10.2139/ssrn.5358801>

#### Summary of the Empirical Research

The third empirical study examined how structured textual interventions influence ecodriving behaviour, knowledge and the perceived quality of action regulation. In a field experiment, participants were randomly assigned to one of three groups: (1) a control group receiving no information, (2) a group receiving generic ecodriving tips, and (3) a group receiving know-how-and-why tips. While generic tips offered surface-level behavioural rules (e.g., “Brake early to avoid harsh braking”), the elaborative tips aimed to embed rules in if–then logic that clarified the underlying technical and causal mechanisms behind behavioural strategies. To capture the impact of these interventions, the study assessed both subjective and objective outcomes. Subjective measures included perceived ecodriving knowledge and perceived

support of action regulation, operationalised along key usability dimensions—effectiveness, efficiency, and confidence—across four stages of information processing, as well as perceived support of the *mental model*, and perceived uncertainty due to a lack of knowledge. Objective driving performance measures were gathered through energy consumption, pedal behaviour, and speed along a predefined driving route.

Regarding driving behaviour, the group with know-how-and-why tips exhibited the lowest mean and standard deviation of throttle position, while the control group showed the highest values. However, no significant linear contrasts were observed for other behavioural indicators, including braking pedal pressure, or speed. Mean energy consumption showed a significant linear trend with the lowest values in the know-how-and-why group.

Subjectively, participants in the know-how-and-why group showed the highest gain in perceived ecodriving knowledge, followed by the generic and control groups. Selective effects were observed in perceived support of action regulation: significant linear contrasts emerged for (a) effective, efficient, and confident regulation; (b) information acquisition, information analysis, and action implementation; as well as (c) support of the mental model, again favouring the know-how-and-why condition. However, no significant linear contrasts were found for decision selection and perceived uncertainty due to lack of knowledge.

Together, these results suggest that know-how-and-why feedback improves understanding, average energy consumption and aspects of experienced and behavioural action regulation.

### **Contribution to the ROs**

This study makes targeted contributions to all research objectives by examining the impact of structurally different textual feedback approaches on both the subjective and behavioural aspects of ecodriving.

Most directly, it contributes to **RO1** by testing how textual information, either generic or elaborated, shapes drivers' implementation of energy-efficient strategies. The findings suggest that textual information explaining how and why ecodriving strategies can reduce energy consumption, even though improvements were not observed for all behavioural driving metrics such as acceleration, braking, or speed variability.

The study also contributes meaningfully to **RO2** by evaluating how different types of information positively influence the perceived ecodriving knowledge. The findings show that elaborative feedback formats significantly improve perceived understanding, indicating that elaborative rule-based feedback can help drivers understand not just what to do, but why—a

crucial precondition for adaptive behaviour in dynamic systems. This highlights the central role of explanatory structure in fostering deeper integration of system-level understanding.

Concerning **RO3**, the study extends knowledge on the subjective quality of action regulation. Know-how-and-why tips led to the highest ratings on all usability dimensions and most information processing stages (information acquisition, information analysis, action implementation). At the same time, no significant effects emerged for decision selection or perceived uncertainty due to lack of knowledge. Drivers perceived know-how-and-why tips as most supportive regarding their *mental model* within action regulation. These findings suggest that know-how-and-why feedback can enhance users' subjective sense of orientation and interpretation. However, this effect may not yet propagate into confident decision selection or fully alleviate uncertainty in the context of a one-time intervention, possibly requiring repeated interaction or active experience across different driving situations.

The study highlights the differentiated impact of elaborate, rule-based feedback: while it enhances perceived understanding, supports quality of action regulation, and reduces energy consumption, it does not automatically yield broad behavioural improvements or reduce uncertainty. This underscores the potential to combine explanatory interventions with real-time, situationally grounded feedback to foster both comprehension and consistent behavioural implementation. A longer consolidation and practice phase might have been necessary to stabilise complete behavioural adaptation.

### **Author contribution**

I contributed by conceptualising the experimental design and evaluation strategy, conducting the formal data analysis, creating the visualisations, and writing the manuscript. Elise Banach contributed by co-developing the study design, preparing and conducting data collection within her master's thesis, and supporting literature research. Markus Gödker supported the conceptual and methodological development and the project organisation and supervised the master's thesis. Jan Heidinger supported the preprocessing of the driving data and provided software support. Lukas Bernhardt implemented the technical setup, including hardware and software components. The study was conducted as part of the ECO.SHARE and HI Lübeck projects under the supervision of Thomas Franke. Student research assistants, Bennet Hut, Maike Steffen and Florian Vierkant, supported data collection and assisted on the software side by enabling the visual selection of driving data and the assignment of subtracks.

**CRedit statement:** **Vivien Moll:** Conceptualisation; Data Curation; Formal Analysis; Methodology; Visualisation; Writing – Original Draft; Writing – Review & Editing. **Elise Banach:** Conceptualisation; Investigation; Methodology. **Markus Gödker:** Conceptualisation; Project

Organisation; Methodology; Writing – Review. **Jan Heidinger:** Data Curation (pre-processing of driving data); Software; Project Organisation. **Lukas Bernhardt:** Software and Hardware (technical implementation). **Thomas Franke:** Conceptualisation; Funding Acquisition; Resources; Project Administration; Supervision; Writing – Review & Editing.

#### 4.4. Study 4: Explaining Ecodriving Recommendations

##### Summary of the Empirical Research

Study 4 examined how different ecodriving feedback approaches influence driving performance, perceived support of the *mental model* and action regulation, subjective information processing awareness (SIPA; Schrills et al., 2024; Schrills & Franke, 2023), and workload. In a controlled driving simulation experiment, participants were randomly assigned to one of three conditions: (1) a control group with a standard consumption display based on common BEV dashboards, (2) a recommendation group also receiving visual speed recommendations, and (3) an explanatory group receiving the same visual displays with auditory if-then-because rules (know-how-and-why) designed to support *mental model* formation and action regulation. The explanatory condition was based on the premise that translating energy-efficiency principles into simplified causal rules can enhance drivers' cognitive representations of system behaviour. However, this simplification may also impose cognitive costs, especially under real-time driving demands.

Across several dependent variables, the findings revealed a differentiated pattern:

- Driving performance: Support was found for the hypothesis that explanatory feedback improves ecodriving behaviour. Significant improvements were observed for mean and total energy consumption as well as mean brake and throttle pedal positions, all favouring the explanatory condition. However, no significant linear contrasts were found for mean acceleration or speed, indicating that performance benefits were selective.
- Gain in perceived (verbalisable) knowledge: All groups exhibited knowledge gains from pre- to post-test in self-reported (verbalisable) ecodriving knowledge. However, no significant group differences or interactions were observed, suggesting that knowledge improvements were not attributable to the feedback approach.
- *Mental model* support: Only the explanatory feedback significantly improved perceived support of the *mental model* compared to the control condition, indicating benefits of auditory tips.
- Perceived support of action regulation: Perceived support in most usability dimensions and later-stage information processing (information analysis, decision, implementation)

did not differ across groups. However, participants in the explanatory group reported significantly lower support for information acquisition than those in the control group, hinting at a trade-off between depth of explanation and accessibility.

- Subjective information processing awareness: Participants in the explanatory condition reported significantly lower SIPA scores than the control group, suggesting reduced system transparency, possibly due to increased cognitive load or a mismatch between recommendations, explanatory feedback, and drivers' *mental model*.
- Driving activity load: Consistent with expectations, the explanatory condition was associated with the highest DALI scores, while the control condition showed the lowest. This supports the notion that auditory rule-based feedback increases task demands.

These findings demonstrated that rule-based, explanatory auditory feedback can enhance *mental model* support and driving performance. However, this benefit came at the cost of increased workload, lower perceived support for information acquisition and lower SIPA. This suggests that optimising the balance between explanation richness and cognitive efficiency remains a critical design challenge for real-time driver feedback systems.

### Contribution to the ROs

This study provides differentiated contributions to all three ROs by comparing a standard consumption display, a recommendation display, and an enhanced explanatory feedback system in a simulated driving environment.

Regarding **RO1**, the study offers support for the effectiveness of explanatory know-how-and-why feedback in implementing energy-efficient driving strategies. Participants in the explanatory condition showed significantly reduced mean and total energy consumption, as well as lower mean brake and throttle pedal positions compared to the other groups. However, these improvements were not mirrored across all driving indicators, as no significant effects emerged for acceleration or speed. This suggests that rule-based explanatory feedback can facilitate smoother and more efficient driving behaviours, but its influence may be restricted to specific dimensions of vehicle control.

About **RO2**, all groups demonstrated substantial self-reported (verbalisable) ecodriving knowledge gains from pre- to post-test. However, no differences between feedback conditions were observed. This indicates that regardless of type, feedback presence alone was sufficient to foster perceived knowledge, potentially due to participants' general engagement with the task or the cumulative effect of simulator experience. As a result, the study contributes to RO2 by highlighting the limitations of differentiated feedback in enhancing (verbalisable) knowledge under constrained exposure conditions.

Concerning **RO3**, which focuses on the quality of action regulation, the study provides a more differentiated picture. Participants in the explanatory condition reported significantly greater perceived support of the *mental model* compared to the control group. However, support for early-stage information processing (information acquisition) was perceived as lower in the explanatory group, possibly due to increased cognitive demands. All usability dimensions and later stages of action regulation showed no significant differences. These findings suggest that while explanatory feedback can increase perceived support for understanding, it may simultaneously introduce accessibility or processing burdens that impair other facets of action regulation. Moreover, lower SIPA scores and higher DALI scores in the explanatory group further indicate that such cognitively rich interventions require careful consideration of their cognitive cost-benefit balance.

### Author contribution

I contributed by developing the research idea, conceptualising the study design, the questionnaire scales, and the evaluation strategy. I conducted the formal data analysis, prepared the visualisations, and wrote the manuscript, with supervision provided by Thomas Franke. Jan Heidinger and Steffen Schmees contributed to this research through pre-processing of driving data and software support. Lukas Bernhardt coordinated the project and was involved in the technical implementation.

Please note that this research was conducted as part of the AMORi project and was only possible through the contribution of the entire AMORi team, including Lukas Bernhardt, Steffen Schmees, Jan Heidinger, Elise Banach, Anne Tichy, Leonardt Wagner, Tobias Harms, Lennart Homann, and others. I collected the data with significant assistance from student research assistants. The technical implementation of the laboratory study setup—including the driving simulator, route sectors, data processing routines, study management system, and display configuration—as well as data collection, was carried out by the AMORi team. Discussions with Tim Schrills on XAI further supported the theoretical and conceptual foundation of the study.

**CRedit statement:** **Vivien Moll:** Conceptualisation; Data Curation; Formal Analysis; Investigation; Methodology; Validation; Visualisation; Writing – Original Draft; Writing – Review & Editing. **Steffen Schmees:** Data Curation; Resources; Software; Writing – Review & Editing. **Jan Heidinger:** Data curation; Software; Writing – Review & Editing. **Lukas Bernhardt:** Project Administration; Resources. **Daniel Görge:** Funding Acquisition; Project Administration; Supervision. **Thomas Franke:** Conceptualisation; Funding Acquisition; Resources; Project Administration; Supervision; Writing – Review & Editing.

## 5. Study 1: Biased Energy Efficiency Perception Based on Instantaneous Consumption Displays – Indication for Heuristic Energy Information Processing

### 5.1. Abstract

Instantaneous consumption displays (ICDs) can be used as central information source to perceive the energy efficiency of manoeuvre-level driving. A key question is whether drivers who use ICDs can accurately derive energy efficiency differences of different driving strategies based on ICDs. There is reason to assume that drivers' consumption judgements may be biased, similar to driving-related phenomena like the time-saving bias. Therefore, the aim of the present research was to examine drivers' accuracy in deriving average consumption from dynamic ICD sequences. Participants viewed videos of a schematic ICD in a controlled experiment where the maximum instantaneous consumption systematically varied over time. Participants ( $N = 55$ ) overestimated the average consumption values. The empirical ranking of the sequences did significantly correlate with the heuristic but not with the correct efficiency ranking. The current study incorporated multilevel modelling due to the nested structure of the data. The estimation difference was greater with higher peak height and shorter peak duration. The effect of peak height on estimation difference weakened with longer peak duration. In sum, the results indicate that ICDs can create biased perceptions of energy efficiency and that drivers seem to use simplifying heuristics. Knowledge and affinity for technology interaction appear to relate to biased estimations, whereas the intensity of prior experience with consumption displays seems irrelevant. Further studies should test other interfaces with debiasing potential such as manoeuvre-based aggregation or fading-trace approaches. Moreover, studies are needed that enable modelling of the effects of more natural temporal-spatial visual attention distribution (e.g., in a driving simulator setting).

**Keywords:** Biased perception, Heuristics, Instantaneous consumption displays, Data visualisation, Energy efficiency

### 5.2. Introduction

Drivers are a critical factor regarding whether a vehicle's energy efficiency potential can be achieved in real-world usage (Barkenbus, 2010). Electric drivetrains in particular are highly susceptible to variations in everyday operational driving behaviour (Sivak and Schoettle, 2012). Drivers continuously adapt their behaviour to balance different driving goals (Dogan et al., 2011). From an analytical standpoint, one can assume that, at the most basic level, drivers want to reach their destination safely, on time, without excessive cognitive workload or stress, without significant financial losses (e.g., speeding tickets, vehicle damage, or excessive fuel/energy consumption), and without disturbing other road users or passengers with the resulting driving style. While avoiding crashes is assumed to be the primary goal, a secondary goal might be to drive as energy-efficient as possible for environmental (e.g., reducing personal carbon footprint; Wiedmann and Minx, 2008) or financial considerations (e.g., because of increasing energy costs).

Drivers' key challenge in controlling their operational (Michon, 1985) eco-driving behaviour to maximise energy efficiency is to determine which driving behaviour is the most energy-efficient at different times and then control the vehicle accordingly. Control-theoretical models of driver behaviour assume that continuous monitoring of goal-oriented behaviour is required to successfully manage the driving task (Fuller, 2005; Summala, 2007). This also applies to the driving objective of increasing energy efficiency (Franke et al., 2016). The essential basis for this dynamic control process is the perception of relevant environment variables, and, as the perceptibility of energy efficiency via visual or noise cues from the environment is limited, energy displays play a key role for this first step in controlling of energy-related driving behaviour. Based on perception of the energy-related facets while driving via consumption displays, the driving behaviour has to adjust within each driving manoeuvre. Indeed, 52% of interviewed hybrid electric vehicle drivers (Franke et al., 2017) monitor consumption displays to derive the energy efficiency level from different driving strategies.

Generally, consumption displays can convey abstract or concrete feedback. In the context of action regulation, these different types of feedback can be attributed to various aspects of the adaptive control of eco-driving strategy selection (see Franke et al., 2016). As the present research focuses on acquiring eco-driving knowledge and identifying applicable energy-efficient strategies, concrete numeric feedback (e.g., instantaneous consumption displays) is the central aspect. It aims to teach individuals how to accelerate efficiently (manoeuvre-level) because it is constantly obvious which behaviour promotes eco-driving (Dahlinger et al., 2018). In contrast, abstract feedback uses rather unclear, symbolic representations of aggregated information to make the reason why one should drive energy efficiently salient (Dahlinger et al., 2018). Instantaneous consumption displays (ICDs), in particular, represent the central, immediate and salient information source (i.e., system variable) within the monitoring process. By way of this process, the driver can determine the energy efficiency of individual driving manoeuvres. The most basic driving manoeuvre in this respect is speed regulation through accelerations (longitudinal vehicle control). Compared to other displays, ICDs provide a large bandwidth of information, a high salience, and a high value due to immediacy. Only ICDs represent the actual acceleration and situation-related influences, while a further aggregation (e.g., average or total consumption) also typically includes manoeuvre-irrelevant information.

However, whether drivers can ultimately derive the situation-specific influence of their driving style through ICDs depends on the accuracy of the subjective temporal integration of the consumption parameter presented. This integration leads to a manoeuvre-based and situation-specific aggregated consumption as measure of energy efficiency of the particular acceleration. Therefore, the key question is how drivers perceive the magnitude dynamics of an

ICD and how accurate the aggregated estimates of energy efficiency are based on these dynamics. Surprisingly, little research exists regarding dynamic magnitude perception in the context of eco-driving with a few exceptions in other facets of the driving task such as speed perception (e.g., Svenson, 1976; Svenson and Salo, 2010). While a glimpse can be sufficient to check if a speed limit is adhered to, the dynamic process must be taken into account when it comes to regulate consumption. And of course, drivers cannot constantly focus on consumption displays and often perceive them peripherally. It is important to understand how this limited perception or somewhat incomplete information processing can lead to inaccurate energy efficiency estimations. Hence, to address this issue comprehensively, different empirical studies are needed. A first line of studies has to identify possible estimation errors regarding the basic perception of dynamic magnitudes with driving-like characteristics. A second line of studies must consider more ecological valid glance patterns and how previously identified biases are influenced by different display components (e.g., driving simulator setting with occlusion paradigm; Gelau et al., 2009; Gelau and Krems, 2004). Of course, individual differences have to be taken into account – both with regard to perceptual variables (first line of studies) and to behavioural variables like driving characteristics (second line of studies). The current paper is the first step towards focusing primarily on the dynamic component variation to identify perceptual phenomena or biases. To investigate the possible influence of the dynamic components of ICDs (e.g., magnitude and time), a study design with sufficient power in a multilevel approach and therefore a sufficient variation of the ICD's components is required. Hence, the initial controlled experiment needs to reflect a kind of ideal state (continuous view) as a baseline, which is comparable to driving on level 2 (i.e., driving autonomously with enough time to look at the display).

Consequently, by first understanding the possibly biased perception of ICDs, we can identify potential approaches for display design and finally better support drivers and their correct development of *mental models* (see also Pampel et al., 2015). As drivers' *mental models* of energy efficient strategies like accelerations differ (e.g., Franke et al., 2016), it is likely that drivers' perception of energy dynamics based on inter-individual difference variables such as knowledge, experience and general cognitive and behavioural styles in interaction with technology differs as well.

Hence, the objectives of the present research are to examine (1) whether drivers can correctly rank the magnitude dynamics in ICDs with regard to energy efficiency, (2) to what extent distortions exist in deriving the manoeuvre-based average consumption from different ICD dynamics, and (3) whether inter-individual difference variables play a role regarding the derivations' quality.

### 5.3. Background

#### Biased magnitude perception in driving

To accurately derive an overall energy efficiency value for a specific driving manoeuvre through monitoring ICDs, a completely rational evaluation would require the integration of instantaneous consumption over a given time. All instantaneous consumption values must be totalled across acceleration time (manoeuvre-based total consumption) and then divided by the number of values (manoeuvre-based average consumption). It is certainly more likely that human judgements in everyday dynamic environments such as driving will rely more on heuristics (i.e., *bounded rationality*; Simon, 1957, 1982). Since people have a limited capacity to evaluate and process available information and usually rely on simplifying heuristics when making intuitive judgements, everyday judgements are often biased in various ways (e.g., Tversky and Kahneman, 1974). One exemplary heuristic in the broader context of magnitude perception is the tendency to automatically assume a linear relationship in various situations when detecting a functional relationship between different values is required. However, this effect can be mediated for example by additional graphic material (Van Dooren et al., 2008), previous experience with non-linear relationships (Christandl and Fetchenhauer, 2009; Keren, 1983) or changes in displayed units (Eriksson et al., 2015; Larrick and Soll, 2008; Peer and Gamliel, 2013). As an example from a driving context, people adopt linear strategies as opposed to considering the curvilinear relationship between speed and travel time (e.g., Peer and Gamliel, 2012, 2013; Svenson, 2008, 2009). Specifically, this means that time saved is underestimated when increasing speed from a relatively low starting point. At a relatively high speed, however, the time saved by a speed increase is overestimated. Similarly, people often assume that the amount of gas consumed relative to fuel efficiency, when expressed as miles per gallon (MPG), will decrease as a linear function (Larrick and Soll, 2008). However, the actual relationship between the amount of gas consumed and a vehicle's MPG value is curvilinear. This may cause undervaluation of small MPG improvements and overvaluation of higher MPG improvements. Hence, there is a pattern that judgements based on non-linear relationships and on values with different magnitudes are simplified and biased.

Nevertheless, studies examining the integration of dynamic magnitude information over time would be more relevant for the objective of the present research. Unfortunately, to the best of the authors' knowledge, no studies currently exist that examine such dynamics in the context of consumption displays. A first line of research in this direction addresses temporal integration of magnitude information in speed perception. Here, the perception of a vehicle's average speed seems dependent on speed magnitude (Svenson, 1976). Furthermore, a higher speed is given too much weight when judging average speed with different combinations of original and

reduced speeds over a certain distance (Svenson and Salo, 2010). However, these studies used static scenarios with written descriptions of scenarios/stimuli instead of letting participants experience dynamic situations. Considering the biased calculation of average speeds (Svenson, 1976; Svenson and Salo, 2010), the displayed amount and duration of consumption may also play a role when judging the average over a given time in a dynamic scenario.

As in many domains of human performance and cognitive biases (e.g., Carnevale et al., 2011; Hoppe and Kusterer, 2011; Ingre et al., 2006; Tett et al., 1991) it can further be assumed that considerable inter-individual differences regarding magnitude perception will exist. Unfortunately, inconsistencies exist in research as some evidence supports (Eriksson and Svenson, 2012) an influence of inter-individual differences in (magnitude) perception biases in driving whereas some does not (Peer and Solomon, 2012; Svenson, 2009). Eriksson and Svenson (2012) asked students and truck drivers to intuitively estimate the average fuel consumption (l/100 km) when increasing (70, 80, 90, 100, 110 and 120 km/h) or decreasing (110, 100, 90, 80, 70 and 60 km/h) speed (one speed change per problem). Participants also received the average consumption of the specific reference speed (60 km/h or 120 km/h). Truck drivers underestimated the fuel saving effect of decreasing speeds. While their judgments regarding increasing speeds were more accurate, students overestimated the fuel consumption. Regardless, changing speeds were presented statically and the influence of acceleration on energy consumption was not considered. Nevertheless, it can be assumed that specific experience and knowledge could influence accurate perception of consumption. However, Peer and Solomon (2012) showed different results: Taxi drivers were just as biased as non-professional drivers regarding speed judgements, journey time and time saving. Furthermore, education and training (physics, engineering) also do not seem to reduce bias regarding time savings, accident risk, and the speed while braking when hitting an object (Svenson, 2009). In sum, the inconsistent results indicate that inter-individual differences may influence several simplified and biased judgements in the context of driving (e.g., speed, consumption in static scenarios, travel time).

### **Graphical magnitude perception**

Although little research on magnitude perception in driving exists, there is ample research in psychophysics and graphical perception regarding static data visualisation (e.g., Cleveland and McGill, 1984; Falmagne, 1971; Hollands and Spence, 1992; Stevens, 1957). For example, research has shown that height differences are more likely detected in “framed rectangles” compared to when non-framed “bars” are used for visualisation (*Weber’s law*; Baird and Noma, 1978; Cleveland and McGill, 1984). Moreover, change can be perceived faster and more accurately in bar and line charts than in pie charts or tiered bar graphs (Hollands and Spence,

1992). And Díaz et al. (2018) found that the perception accuracy of absolute values is better when using quantised gradients (opacity changes every 25%) and Tufte's (1986) gridlines (inner line every 25%) compared to standard solid bars. In this context, boxed bars or a top gridline also improved perception accuracy compared to a basic chart frame. However, since ICDs are dynamic rather than static visualisations of data, these findings are not necessarily applicable to the perception of ICDs.

To the best of the authors' knowledge, there seems to be little research regarding animated (i.e., dynamic) data visualisation comparable to static data visualisation. Wu, Jiang, Xu, and Nandi (2016) first examined perceptual accuracy in animated data visualisations and emphasised the need for further controlled studies. They showed that the maximum height of an animated bar (peak height) improved estimation accuracy about the time position of the peak and rate of change of the animation (varying slope). However, higher peaks seemed to increase bar height estimation error (Wu et al., 2016). Previous research on animated data visualisation have focused on different topics such as possible benefits provided by animated data (e.g., Heer and Robertson, 2007), different animation styles (Merz et al., 2016), animated graphics to teach complex systems (Tversky et al., 2002) or animated images (Gonzalez, 1996). These topics have been studied in various contexts such as trends (Robertson et al., 2008), influence on decision making (Gonzalez, 1996) and user experience (Merz et al., 2016) or transitions of static data (Heer and Robertson, 2007). For example, Herr and Robertson (2007) showed that animated transitions of static data visualisations enhance graphical change perception. Thus, the dynamic magnitude perception seems biased. However, the concrete transfer is lacking in the context of driving (or rather energy perception).

### 5.4. Present Research

The present research is part of a more complex research agenda to better understand how displays can optimally support the perception of energy-efficient driving styles. The objective was to examine how varying ICD characteristics influence the derivation of manoeuvre-based average consumption as measure for energy efficiency. In this context, the perception accuracy (estimation difference of average consumption) was considered. Given the limited amount of data and considering the previous research approach regarding graphical perception in animated data visualisations (see Wu et al., 2016), the present research was largely exploratory. The following research questions were examined:

**RQ1:** Can drivers rank the various dynamics of a schematic ICD in the correct order of energy efficiency for acceleration manoeuvres?

**RQ2:** Do any biases exist in the perception accuracy of energy efficiency based on the dynamic magnitude characteristics?

**RQ3:** Do inter-individual difference variables impact the perception accuracy of energy efficiency?

Because it is atypical in driving to accurately estimate the exact manoeuvre-based average consumption when comparing different driving manoeuvres, RQ1 asked for the correct ranking order. RQ2 addressed the possible transfer of previous findings regarding judgement biases in the driving context (see section 2.1) on the perception of consumption. As people showed a peak-height-bias in animated bar charts (Wu et al., 2016) and gave faster speeds too much weight (Svenson, 1976; Svenson and Salo, 2010), a rational assumption is that the peak height influences the estimation difference. In addition, the peak duration at higher peaks is lower to achieve a certain average consumption. Therefore, it could be assumed that an effect of peak duration and an interaction between peak height and peak duration exists.

In RQ3, three inter-individual variables that presumably impact the perception of and interaction with technology were considered: general knowledge, concrete practical experience and stable interaction styles (i.e., personality). Since the influence of experience on judgements of average consumption is unclear (Christandl and Fetchenhauer, 2009; Eriksson and Svenson, 2012; Svenson, 1976; Svenson and Salo, 2010), a direct and specific facet was considered with respect to system interaction: experience with consumption displays. Technical-mathematical knowledge was also considered a variable since system knowledge influences the perceived strategy effectiveness (i.e., driving strategy, Franke et al., 2016) and is acquired with system interaction (Franke et al., 2017). Furthermore, knowledge-based level of behaviour (see Rasmussen, 1983) is particularly important if someone is a novice regarding energy-efficient driving. This is true for novice drivers as well as people new to certain vehicle types (e.g., electric vehicles). Besides, technical-mathematical knowledge could promote the comprehension of data aggregation over time. This comprehension is essential in estimating average consumption. Besides experience and knowledge, the affinity for technology interaction (ATI) scale served as an exemplary facet of general cognitive and behavioural styles in technology interaction. The scale was developed based on a review of literature between 1982 and 2016 on individual personality traits that influence interacting with new technical systems (Attig et al., 2017). In the broader context of biases regarding non-linear relationships, need for cognition (Cacioppo and Petty, 1982) and therefore a stronger motivation to solve estimation tasks for example seem to positively influence the underestimation of exponential growth (Christandl and Fetchenhauer, 2009). A high ATI as a dimension of need for cognition and therefore more actively exploring systems (in this case, consumption displays) may lead to better estimations based on information aggregation.

## 5.5. Method

### Participants

A total of 58 participants were recruited via a psychology student email distribution list and via social media. Three participants were excluded because they mistook the ICD for a display of speed. Participants in the resulting sample ( $N = 55$ ) had an average age of  $M = 22.55$  years ( $SD = 3.84$ ). Within the sample, 86% were female and 87% were psychology students. Their average driving experience was 4.68 years ( $SD = 3.36$  years) and 52.98 km ( $SD = 97.21$  km) per week.

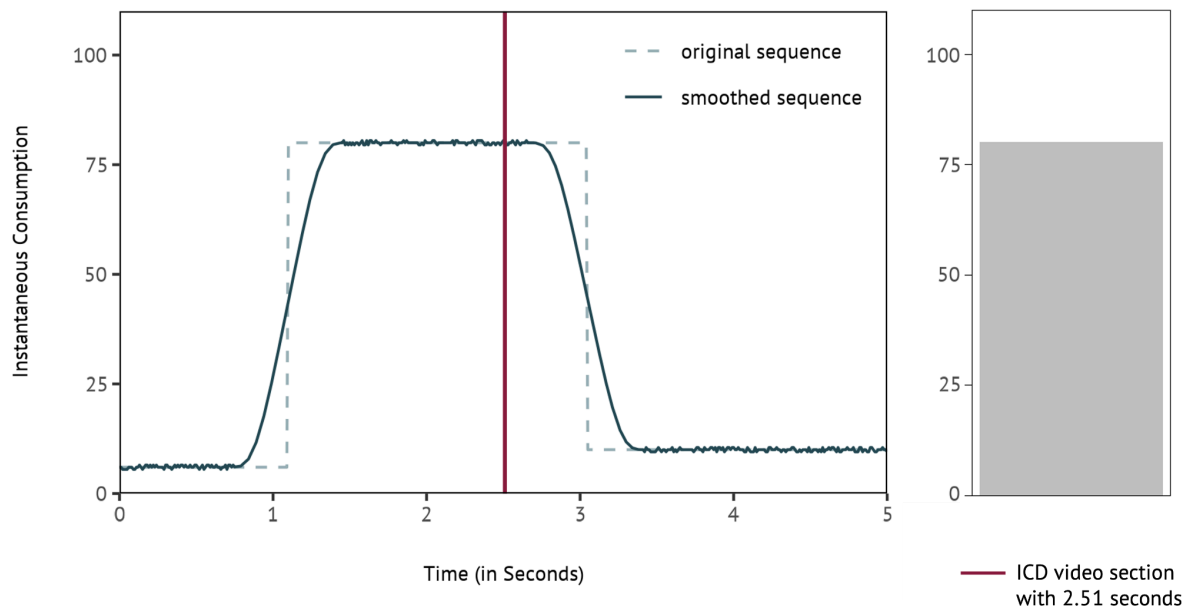
### Stimulus material

To examine the perception of ICDs during acceleration, schematic sequences of energy consumption during periods of acceleration were created. The acceleration's basic elements include an initial consumption rate at a constant start speed, an end consumption rate at a constant target speed and a sharp increase of consumption rate depending on acceleration intensity and speed. Despite the schematic construction of the sequences, considerable efforts were invested to create similar energy dynamics to real-world consumption in electric vehicles. Specifically, we used Galvin's (2017) work to define realistic values. According to Galvin (2017), the consumption of a typical compact electric vehicle (i.e., Kia Soul Electric 2015) is 11.1 kWh/100 km at a constant speed of 20 km/h, 13.4 kWh/100 km at a constant speed of 80 km/h, and 73 kWh/100 km within a typical acceleration ( $1.35 \text{ m/s}^2$ – $1.4 \text{ m/s}^2$  within a speed range of around 50–80 km/h). Hence, the values' ratio used in the schematic sequences created for the present experiment is comparable to real-life energy consumption of battery electric vehicles.

Twenty-five sequences lasting 5 s and with a temporal resolution of 100 Hz were created, forming five groups of different average consumption values (32, 34, 36, 38, 40) with five different peak values each (100, 90, 80, 70, 60). The consumption unit was fictional to enable broader generalisation. All sequences began with the same starting consumption value (6) and ended on the same value as well (10). Peaks always began at 1.1 s and continued for the needed duration to achieve the targeted average consumption of the sequence given the defined peak height. Hence, the higher the peak, the shorter the sequence of the peak had to be to result in the same average consumption. To increase realism and to ensure a comparable rate of change, a Lowess smoothing (Cleveland, 1979) with a smoother span of  $f = 0.15$  was conducted for all sequences. Furthermore, noise ( $\pm 0$  or  $\pm 0.5$  with a respective probability of 50%) was added to the constant consumption phases to underline the ongoing dynamic process and increase the simulation authenticity (see Fig. 1).

**Fig. 1**

*Example of one smoothed sequence after adding noise (average peak height = 80, average consumption = 36)*



All sequences varied in peak duration (see Table 1). The peak durations included the display time of the respective average peak value ( $\pm 0.5$ ). R (R Core Team, 2020) and the animation (Xie, 2013) package were used to create the schematic ICD videos in the form of an animated bar plot (see Fig. 1). Besides this bar plot on a white background, no further information was shown in the videos. The bar plot's frame size in the presented videos on LimeSurvey (LimeSurvey GmbH, n.d.) was  $342 \times 114$  pixels (height  $\times$  width). Just prior to the actual sequence, a fixation cross was displayed in the middle of the video screen for 1.5 s. After the sequence occurred, a white screen was shown.

## Procedure

The experiment was conducted online with LimeSurvey (LimeSurvey GmbH, n.d.) and the setup was not controlled between individual participants. As a general scenario, participants were asked to imagine a traffic situation in which they accelerate the vehicle after the end of a previous speed limit. An example sequence including the average parameters of all sequences (average consumption = 36, peak = 80) was presented to explain the dynamics of consumption (start consumption level, maximum consumption level, end consumption level) and to familiarise participants with the ICD videos. The participants were told that the consumption unit was fictional. This was done to avoid comparisons (e.g., to a more familiar combustion engine) and irritations due to deviations from real and more familiar sequences. The

participants were instructed to estimate the average consumption level for each sequence: “Please estimate the average consumption level on a scale from 0 to 100 consumption units as accurately as possible”. Afterwards, two blocks of 25 sequences each were presented, each block starting with the same first sequence (ID = 1). The further 24 sequences were randomised within the blocks. After completing the experimental trials, participants answered an open-ended question in the following post-experimental questionnaire to determine which cues they based their estimations on and if they understood the task correctly. Furthermore, participants gave sociodemographic information, their experience with consumption displays, their technical-mathematical knowledge and their ATI. Participation in the entire online study lasted an average of 30 minutes.

**Table 1**

*Sequence Design*

Sequence ID	Average consumption	Average peak height	Peak duration (in s) *
22	32	60	1.75
18	32	70	1.35
14	32	80	1.08
10	32	90	0.86
6	32	100	0.69
23	34	60	1.94
19	34	70	1.52
15	34	80	1.21
11	34	90	0.99
7	34	100	0.80
5	36	60	2.15
4	36	70	1.69
3	36	80	1.36
2	36	90	1.12
1	36	100	0.91
24	38	60	2.35
20	38	70	1.86
16	38	80	1.51
12	38	90	1.25
8	38	100	1.03
25	40	60	2.55
21	40	70	2.03
17	40	80	1.65
13	40	90	1.37
9	40	100	1.14

*Notes.* \*Peak duration refers to the smoothed sequences and an average peak  $\pm 0.5$

## **Scales and measures**

According to common practice (e.g., Cripps, 2017), Cronbach's alpha was interpreted as poor ( $.5 \leq \alpha < .6$ ), questionable ( $.6 \leq \alpha < .7$ ), acceptable ( $.7 \leq \alpha < .8$ ), good ( $.8 \leq \alpha < .9$ ), or excellent ( $\alpha \geq .9$ ) for all measures. Scales in the post-experimental questionnaire contained a 6-point Likert scale ranging from 1 = "completely disagree" to 6 = "completely agree", if not stated otherwise.

### *Estimation difference*

For the dependent variable, the difference between the participants' empirical estimates and the correct average consumption levels was calculated as a measure of perception accuracy/estimation error (0 = perfect estimate, > 0 overestimation, < 0 underestimation of average consumption levels). Test-retest reliability of the mean estimation difference between block 1 and 2 was excellent ( $\alpha = .97$ ). Even when considering individual sequences, test-retest reliabilities were all acceptable ( $\alpha > .70$ ) with an average  $\alpha$  of .89. The mean estimation difference was  $M = 4.92$  ( $SD = 11.33$ , range = 49.48).

### *Experience with consumption displays*

Experience with consumption displays was assessed via eight items (see Table A1) focusing on attention directed at displays, helpfulness, and specific as well as general relevance of displays to achieve fuel (i.e., energy and gas) efficiency. The reliability of the means of all item values was excellent ( $\alpha = .92$ ). The average experience with consumption displays was  $M = 3.85$  ( $SD = 1.06$ , range = 4.75), indicating that the sample was neither very experienced nor very inexperienced. Therefore, the conditions were considered optimal, as participants were not exclusively expert or novice (i.e., variance of experience was not limited).

### *Affinity for technology interaction*

The ATI scale (Franke et al., 2018) consists of nine items. The ATI score is computed as the mean score of all nine items (Items 3, 6, 8 reversed). The internal consistency of the ATI scale was excellent ( $\alpha = .90$ ). The average ATI in the sample was  $M = 3.21$  ( $SD = 1.01$ , range = 4.22).

### *Technical and mathematical knowledge*

The participants' self-rated technical and mathematical knowledge was assessed by five items (see Table A1). Internal consistency of the knowledge scale was acceptable ( $\alpha = .77$ ). The average score of knowledge was  $M = 2.74$  ( $SD = 0.98$ , range = 4.83).

## 5.6. Results

The significance level was set to  $\alpha = .05$  for all analyses. Based on Arend and Schäfer (2018), we estimated that the present study design yielded sufficient power (i.e.,  $\geq .80$ ; cf. Cohen, 1988) to detect small to medium L1 direct effects in a multilevel approach. Similarly, we assumed medium to large effects for the L2 direct and cross-level interaction effects.

### Heuristic energy efficiency ranking

Estimation differences were not normally distributed as assessed by the Shapiro-Wilk-Test ( $p < .05$ ). Therefore, a Kendall rank correlation between the empirical and the correct ranks were computed for each block to test if drivers can rank the various dynamics of a schematic ICD in the correct order of energy efficiency for acceleration manoeuvres (**RQ1**). Significant correlations were non-existent in both block 1 and block 2 ( $r_t = .16, p = .293$  and  $r_t = .13, p = .389$ ). Thus, it seems participants did not correctly order the ICD scenarios. In addition, open-ended comments from 15 participants indicate that heuristics were used without accounting for the dynamic process (e.g., “Comparison of the starting consumption value with the difference of the consumption value during acceleration”, “Smallest and highest value, calculating the mean”, “Half of the consumption value during acceleration (when the bar moved up)”). Although 35 participants attempted to account for time (e.g., “duration and magnitude of the bar”), it seems they failed to consider the dynamic rise (e.g., “highest level duration, lowest level duration, highest level value, lowest level value”). One participant mentioned considering primarily the value (“Value (primary) and duration”). Another mentioned changing his strategy over time: first taking value and duration into account, then using a simplifying heuristic (“At first, I paid attention to duration and amount of consumption. After some videos, [...] I divided the highest value in half [...]"). Comments from three participants could not be clearly assigned to a category. The mentioned heuristic calculations (e.g.,  $\text{peak}/2$ ,  $(\text{minimum consumption value} + \text{peak})/2$ ,  $(\text{start consumption value} + \text{end consumption value} + \text{peak})/2$ ) result in a different ranking than the correct ranking. We computed a Kendall rank correlation between the empirical and heuristic ranks for each block, showing significance in both block 1 and block 2 ( $r_t = .91, p < .001$ ). In sum, although the empirical ranking seems not to reflect the correct ranking, it better fits a heuristic ranking. A possible conclusion is that ICDs do not allow for correct recognition of the optimal strategy regarding a specific driving manoeuvre.

### Biased perception of energy efficiency

To test if any biases in the perception accuracy of energy efficiency based on the dynamic magnitude characteristics exist (**RQ2**), the mean estimation difference was compared to perfect

estimation (estimation difference = 0). Prior testing determined whether a difference between the two blocks existed because of possible variations due to motivational changes, learning effects or other reasons. A Wilcoxon signed-rank test indicated a significantly smaller mean estimation difference in block 1 ( $Mdn = 3.76$ ) than in block 2 ( $Mdn = 5.44$ ),  $W = 1034.00$ ,  $z = 2.21$ ,  $p = .027$ , with a small effect size ( $r = .21$ ; Rosenthal, 1994). Therefore, the participants' estimation was more accurate in block 1 than in block 2. Furthermore, a one-sample Wilcoxon signed-rank test showed that the mean estimation differences for block 1 and block 2 were significantly higher than 0 ( $W = 1425.50$ ,  $z = 5.49$  and  $W = 1368.00$ ,  $z = 5.01$ ,  $p < .001$ ). The effect sizes were  $r = .52$  and  $r = .48$ , respectively, corresponding to large and medium effects (Rosenthal, 1994). This shows that the average consumption was overestimated in both blocks.

Following Leckie (2013) as well as Snijders and Bosker (2012), a multilevel model was created to examine possible effects (peak height, peak duration, interaction between peak height and peak duration). Thus far, multilevel models have seldom been employed in traffic psychology, human factors and ergonomics with a few exceptions. A modest number of published articles between 2013 and November 2020 incorporate multilevel models (search for "multilevel model" and screen relevant articles) when compared to the number of all published articles in the particular journal during this time period:  $< 1.7\%$  in "Ergonomics" (e.g., Jung et al., 2017), "Applied Ergonomics" (e.g., Hiemstra-van Mastrigt et al., 2015), "Computers in Human behaviour" (e.g., Kushlev et al., 2019) and in "Transportation Research Part F: Traffic Psychology and Behaviour" (e.g., Molnar et al., 2018). The central advantage of multilevel approaches is that they consider hierarchical or clustered structures in the data, thereby avoiding underestimation of standard errors of regression coefficients in contrast to multiple regression, for example. Ignoring the multilevel data structure may also lead to employing statistical procedures with violated independence assumptions (e.g., dependent observations from the same individual) and unfounded conclusions (for further details, see Snijders and Bosker, 2012).

With a three-level model, the clustered data structure, comprising participants at the highest level (L3), peak height groups at the medium level (L2) and measures at the lowest level (L1) was used to analyse the data. There were 55 participants at L3, (5 peaks  $\times$  55 participants  $=$ ) 275 peak height groups at L2 and (5 observations per peak height group  $\times$  2 blocks  $\times$  275 peak height groups  $=$ ) 2750 measures at L1. We used R (R Core Team, 2020) with *lme4* (Bates et al., 2015) package to perform multilevel analyses. First, it was important to test if the empty three-level model fitted the data significantly better than simpler two-level models and the single-level model (Leckie, 2013). A likelihood ratio test showed that the empty three-level model M0 (see Table 2) was preferred to its single-level counterpart L0 ( $\chi^2_2 = 3959.36$ ,  $p < .001$ ).

To test the null hypothesis that no effects of peak height group exist, M0 was compared to the simpler two-level measures-within-participants model T1. M0 was preferred to T1 ( $\chi^2_1 = 1719.17, p < .001$ ). To test the null hypothesis that there are no participant effects, M0 was compared to the simpler two-level measures-within-peak-height-group model T2. M0 was also preferred to T2 ( $\chi^2_1 = 3452.39, p < .001$ ). A multilevel analysis approach was clearly favoured over a single-level (i.e., simple regression analysis) and two-level approach. The empty three-level model reveals the raw within-group and between-group variances, which are useful as a general description and a starting point for further model fitting (Snijders and Bosker, 2012). Calculating the variance partition coefficients and the intraclass correlation helps to determine whether a multilevel model is necessary and to show the degree of data clustering (Leckie, 2013). A total of 54.5% of the variation in estimation difference lay between participants, 28.7% lay within participants between the different peak height groups, while the remaining 16.8% lay within peak groups between the estimation differences (see variance partition coefficient in Table 3). Thus, there was substantial variation between participants and a variation between peak height groups. Finally, the participants' intraclass correlation coefficient (ICC) was .545, while the peak height group ICC was .832. Although ICC values are usually small in practice (Musca et al., 2011), rather large ICC values are expected in a repeated measures design (Arend and Schäfer, 2018). Overall, an ICC of .50 can be considered large (Arend and Schäfer, 2018). As even very small ICCs can dramatically influence Type-I error rate in standard one-level analyses for independent data, a multilevel approach was favoured, where the variation between groups is part of the model (Musca et al., 2011).

The predictor variables (peak height, peak duration), their cross-level interaction as well as their random slopes were added stepwise to model M1 (see Table 2), corresponding to the respective likelihood ratio tests. At L2, there were random slopes for peak height and duration, whereas at L3, they only existed for peak height. M1 showed a significantly better fit to the data than the empty three-level model ( $\chi^2_{10} = 816.10, p < .001, R^2_{\text{marginal}} = .19$  (proportion of variance explained by the fixed factors alone),  $R^2_{\text{conditional}} = .86$  (proportion of variance explained by both fixed and random factors)). The *MuMIn* (Barton, 2018) package was used to compute the  $R^2$  values according to Nakagawa and Schielzeth (2013). The fixed effects of peak height ( $\beta = 0.39, SE = 0.04$ ) and peak duration ( $\beta = -9.92, SE = 0.73$ ) as well as the interaction ( $\beta = -0.18, SE = 0.02$ ; see Fig. 2a) were significant ( $t(137.11) = 8.82, t(64.95) = -13.57$  and  $t(614.82) = -8.12, p < .001$ ). The estimation difference is larger with greater peak height and shorter peak duration. The effect of peak height on estimation difference becomes weaker with longer peak duration. In sum, perception accuracy of energy efficiency is biased based on the dynamic magnitude characteristics (peak height and peak duration).

**Table 2**

*Models*

Model	Equation
L0	$Y_i = \beta_0 + e_i$
T1	$Y_{ij} = \beta_{0j} + V_{0j} + e_{ij}$
T2	$Y_{ip} = \beta_{0p} + U_{0p} + e_{ip}$
M0	$Y_{ipj} = \beta_{0pj} + V_{0pj} + U_{0pj} + e_{ipj}$
M1	<p>L1: <math>Y_{ipj} = \alpha_{0jk} + \alpha_{1jk} \text{duration} + e_{ipj}</math></p> <p>L2: <math>\alpha_{0jk} = \gamma_{00j} + \gamma_{01j} \text{peak} + U_{0pj}</math>  <math>\alpha_{1jk} = \gamma_{10j} + U_{1pj}</math></p> <p>L3: <math>\gamma_{00j} = \beta_{000} + V_{00j} + \beta_{110} \text{duration} \times \text{peak}</math>  <math>\gamma_{01j} = \beta_{010} + V_{01j}</math>  <math>\gamma_{10j} = \beta_{100} + V_{10j}</math>  <math>Y_{ipj} = \gamma_{000} + \beta_{100} \text{duration} + \beta_{010} \text{peak} + \beta_{110} \text{duration} \times \text{peak} + V_{01j} \text{peak} + V_{10j} \text{duration} + U_{1pj} \text{duration} + V_{00j} + U_{0pj} + e_{ipj}</math></p>

**Table 3**

*VPC and ICC statistics*

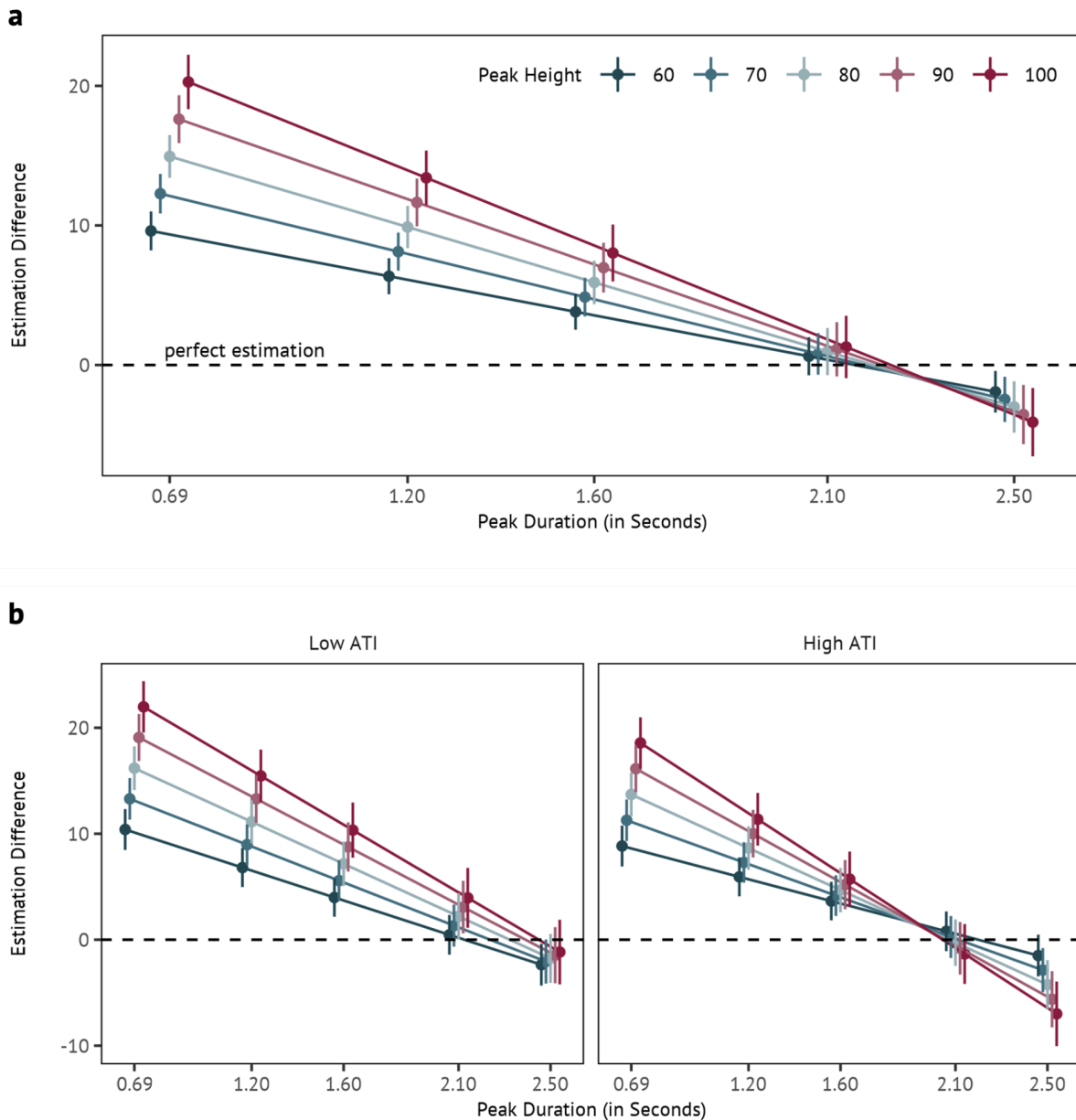
	VPC	ICC
Participants	.545	.545
Peak height group	.287	.832
Measures	.168	

Notes. VPC = variance partition coefficient, ICC = intraclass correlation coefficient.

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Fig. 2

Cross-level interactions



Note. 2a: Cross-level interaction between peak duration and peak height. 2b: Cross-level interaction between peak duration and peak height faceted by ATI ( $M \pm SD = 3.21 \pm 1.00$ ). Standard errors are offset.

### Influence of inter-individual difference variables

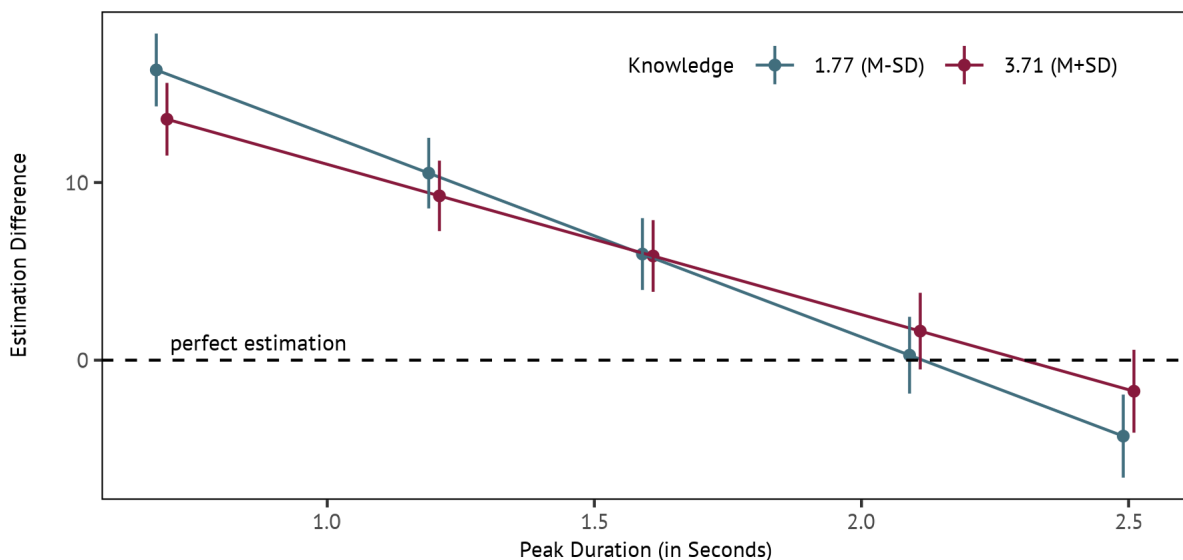
To identify potential inter-individual influencing factors in an exploratory manner (RQ3), the cross-level interactions of each person-level predictor with peak height and peak duration were

considered individually in 9 total models (see Table A2 for the detailed results). To avoid erroneous interpretations, the fixed effects were also included in each case regardless of significance (Snijders and Bosker, 2012). The cross-level interactions between ATI and the L2 predictor peak height as well as the L1 predictor peak duration were significant ( $p < .05$ ). This means that the effects of peak height and peak duration on estimation difference become weaker with higher ATI. Additionally, the interaction between peak height, peak duration and ATI was significant ( $p < .05$ ). ATI influences the peak-height-effect (greater estimation difference with greater peak heights) which decreases with higher peak duration (see Fig. 2b). With high ATI, the effect of peak height on the estimation difference decreases faster with increasing peak duration when compared to a small ATI. Further, it can be surmised that there is a peak-height effect towards underestimation depending on peak duration (i.e., acceleration duration) after reaching a certain peak duration (greater underestimation with taller peak heights).

In addition to the significant effect of ATI, the interaction between knowledge and peak duration was significant ( $p < .05$ , see Fig. 3). The effect of peak duration on estimation difference is weaker with enhanced knowledge. Overall, knowledge and ATI seem to impact estimation biases, whereas experience with consumption displays seems irrelevant.

**Fig. 3**

*Cross-level Interaction Between Peak Duration and Knowledge*



*Note.* Standard errors are offset.

## 5.7. Discussion

### Summary of results and theoretical implications

The objective of the present study was to examine whether drivers can accurately determine efficiency differences of accelerations based on perceiving dynamic ICD sequences. People tend to overestimate the average consumption level when the maximum consumption value is higher and is displayed for less time (i.e., the shorter the acceleration).

The overestimation is comparable to judgements of average speed that depend on speed amount (Svenson, 1976; Svenson and Salo, 2010). The present results also expand Wu et al.'s (2016) findings regarding the lack of accuracy in estimating higher peaks. Thus, drivers cannot correctly integrate information on time and magnitude into their average consumption judgements and therefore into their perception of energy-efficient driving strategies. In addition, open-ended comments from participants indicate that they incorporated simplifying heuristics without account for temporal factors at all (e.g., adding peak and minimum weight divided by 2) or without considering the increase and decrease (= 28% of the sequences on average). A possible explanation for the peak-height effect is that the higher values were more easily available (*availability heuristic*; Tversky and Kahneman, 1973). Furthermore, the fact that the peak is primarily considered but the duration is neglected extends research regarding past affective experiences (*peak-end rule*; Fredrickson and Kahneman, 1993; Kahneman, 2000). By applying the representativeness heuristic (Kahneman and Tversky, 1972), only prototypical moments (i.e., "snapshots") of the entire experience influence judgments (Fredrickson and Kahneman, 1993; Kahneman, 2000). The authors assume that evaluations are determined by a weighted average of peak (most intense moment) and end experience. In the present study, the effect of peak on efficiency judgements depends on duration. Furthermore, the mentioned heuristic calculations of some participants also consider start consumption. All mentioned heuristic calculations (e.g.,  $\text{peak}/2$ ,  $(\text{minimum consumption value} + \text{peak})/2$ ,  $(\text{start consumption value} + \text{end consumption value} + \text{peak})/2$ ) result in a ranking that differs from the correct ranking and significantly correlates with the empirical ranking. The heuristics also fit a real driving situation well, in which only snapshots of the dynamic process are perceived.

Furthermore, the overestimation was higher in block 2 than in block 1. This could have been due to several different reasons. The participants may have become less motivated over the course of the experiment. It is also possible that participants tended to increasingly use simplifying heuristics. One open-ended comment supported this explanation ("At first, I paid attention to duration and amount of consumption. After some videos, [...] I divided the highest value in half [...]").

Further, the peak-height and peak-duration effects are apparently related to inter-individual difference variables such as ATI (Franke et al., 2018). As ATI is a personal resource for coping with technology as well as an interaction style rooted in the construct need for cognition (Cacioppo and Petty, 1982), the latter may fundamentally influence the biased dynamic perception of consumption displays. Therefore, drivers with higher tendencies to cognitively engage with systems might be less biased because of actively exploring consumption displays.

Knowledge influences the perceived strategy effectiveness (Franke et al., 2016) and reduces the peak-duration effect. However, experience with consumption displays does not relate to any biases. This corroborates findings regarding other estimation biases in the driving context (Peer and Solomon, 2012; Svenson, 2009). However, knowledge and experience with consumption displays were self-rated in the present study instead of being objectively measured.

In addition to the overestimation, monitoring of simple ICDs does not lead to a correct ranking of different acceleration sequences regarding their energy efficiency. The incorrect ordering might be due to heuristic estimations and the non-consideration of time or rather the dynamic process. Estimations based on only peak, peak and start consumption values or peak, start and end consumption values better fit the empirical ranking. If drivers are unable to identify the most energy-efficient strategies, they obviously cannot purposefully select and apply them. Future experiments could include a pairwise comparison or consecutively presented sequences with an ordering task ("Which sequence was the most energy efficient?") as indirect alternatives to consumption estimations.

### **Design Implications**

Since judgment biases can be countered (e.g., Eriksson et al., 2015; Larrick and Soll, 2008; Peer and Gamliel, 2013) and interfaces can support drivers during trips (e.g., Lundström and Bogdan, 2017), a fruitful strategy based on the present research is to develop and examine different variants of consumption displays to improve perception of energy efficient driving manoeuvres. It remains unclear if differences in ICD shape (e.g., bar, radial) and other display modes (e.g., digit vs. graphical, scale legend vs. no scale legend, normal scale vs. shrinking scale) could influence how magnitude changes are perceived. Shrinking small values (compared to larger values) could emphasise their proportion within one acceleration manoeuvre and therefore reduce overestimation. Nevertheless, it suggests that simple ICDs are insufficient to optimise energy efficiency. Besides, the high perceptual workload and distraction potential, aggregating magnitude information with duration, remains the main problem regarding eco-driving strategy selection.

Information availability could be improved by providing previous information via a fading trace reflecting magnitude changes through different transparencies and width. Some interfaces already combine graphs of remaining range (in km), consumption over the last x km driven, or average consumption during the last x minutes, providing more information than a real-time snapshot (e.g., Tesla Model S). This approach can provide a clear reference period and encourage the driver to consider magnitude information over time. One very obvious solution for the integration problem is to compute average consumption for each identified driving manoeuvre or situation. This could improve a manoeuvre-specific selection of strategies and focus on the increased energy loss during accelerations due to the energy/distance metric. Using a metric other than energy/distance might also be useful as accelerations should occur at the highest possible conversion efficiency of electric energy invested per kinetic energy gained (for a possible design and further discussion, see Franke et al., 2019).

### **Limitations and further research**

Different from Wu et al.'s (2016) more mathematical-quantitative approach, the present study instead compared a defined set of visualisations. Effects for smaller (<60) or higher (>100) peaks as well as longer peak durations remain unclear. Also, the given scale (0–100) may have created confounded estimations. Furthermore, it must be mentioned that the videos were larger than comparable displays in vehicles. Follow-up studies should closely examine the judgement biases influenced by visual angle. Moreover, the ecological validity of the current study is rather low given it occurred in an artificial setting. Participants may have employed the simplifying approach due to low motivation and/or increasing fatigue. As the setting was not controlled, it is also possible that participants were increasingly distracted. Thus, the setting should be controlled in further experiments. This issue could also suggest that in a more complex and real driving situation, simplifying heuristics are increasingly used to better balance the limited resources of attention. Further studies should take the actual driving behaviour as a dependent variable into account by testing different displays in the driving simulator. In a driving simulator setting various consumption dynamics due to inter- as well as intra-individual differences would also be considered. In contrast, there were only schematic and therefore artificial acceleration styles in the present study due to standardisation. It remains unclear how more realistic driving styles interact with the present biases and how they influence success and adoption of future debiasing displays. At least, it has been shown that the success of support systems can depend on driver characteristics (e.g., Liu et al., 2018). Likewise, it is important to obtain a more representative sample (age, driving experience, ATI) to make definitive statements about the impact of knowledge and experience. The present sample does not perfectly match the general population regarding ATI ( $M = 3.21$ ) as the average ATI score in the population has been reported to be around 3.5 (Franke et al., 2018). The present study centred

on general psychological (perceptual) phenomena and thus systematic glance strategies were not examined. Accordingly, driving experience was not a factor in the present study. Future research should examine glance strategies as they likely differ between experts and novices. Nevertheless, it must be noted that expertise with consumption displays does not necessarily correlate with driving experience as some experienced drivers may rarely use the consumption display. Likewise, some with little driving experience may often use the display. In addition, experience with consumption displays had no influence on the cognitive biases in the present study.

Although not the subject of our current research, abstract feedback could be more appropriate with higher expertise in energy-efficient driving styles, because motivation is then at the crucial level. In this case, an eco-driving learning mode (concrete feedback) and an ecodriving expert mode (abstract feedback) could be integrated. While these assumptions are too dissociated from the present research results, it might prove interesting to investigate the effect of different levels of eco-driving expertise as well as different feedback modes on perception biases, driving behaviour and gaze strategies. Energy consumption also depends on other external factors than driving behaviour (e.g., environmental and traffic conditions, ambient temperature, route type; e.g., Badin et al., 2013; Younes et al., 2013) and on internal factors (i.e., vehicle specifications). But as is well known, the achieved energy consumption of EVs is highly variable and influenced by driver behaviour as central external factor (af Wahlberg, 2007; Barkenbus, 2010; Bingham et al., 2012). It must be mentioned that the present study only focuses on one specific driving behaviour: accelerations. But regained energy can also be visualised through an instantaneous energy display. Besides, regenerative braking already seems to be cognitively biased (energy conversion fallacy; Franke et al., 2016). Many drivers of hybrid electric vehicles seem to assume that it is energy-efficient to actively use and regain electric energy (Arend and Franke, 2017) although regeneration rate does not necessarily lead to maximal driving efficiency (Younes et al., 2013). In sum, there are strong indications that the current biases are also transferable to regenerative braking. The present study is only an initial step to identify approaches for display design and finally better support drivers and their correct development of *mental models*. The following step would be embedding the estimation task that includes different display variants in a driving simulator study (e.g., with an occlusion paradigm; Gelau et al., 2009; Gelau and Kreams, 2004). It is possible to compare various factors on presentation level (shape, size, colour, quantised gradients, Tufte's (1986) gridlines) or completely different display variants (e.g., trace displays, additional aggregated indicator, etc.). It is expected that in a real and more demanding driving situation, the identified biases will have an even stronger influence as heuristics were already used in the present experiment. More precisely, only perceiving display snapshots (in the direct or indirect field of view) might encourage heuristic estimations without accounting for the dynamic process. It appears reasonable to further examine the glance behaviour to

understand which snapshots are perceived in a real driving setting and if these snapshots fit the reported heuristic calculations.

## 5.8. Conclusion

To conclude, a simple visualisation of instantaneous consumption may be insufficient to determine the actual efficiency of different acceleration strategies. The present study revealed heuristics and biases in perception of energy efficiency of driving manoeuvres and potential for improvement—even during continuous monitoring. Therefore, the present research laid the foundation and can serve as a basis for further studies investigating the perception of dynamic data in general, as well as the effect of different dynamics of consumption sequences in particular.

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## 5.10. Appendix

**Table A1**

*Translated Items of Inter-Individual Difference Variables*

Scale name	Item
Experience with consumption displays	When driving, I typically pay close attention to the display of instantaneous consumption in order to save as much fuel as possible.
	The display of instantaneous consumption hardly matters to me when I try to save fuel.
	The display of instantaneous consumption helps me to assess which driving behaviour is fuel-efficient.
	When driving, I typically pay close attention to the display of the average consumption in order to save as much fuel as possible.
	The display of the average consumption hardly matters to me when I try to save fuel.
	The display of the average consumption helps me to assess which driving behaviour is fuel-efficient.
	Overall, I intentionally use displays while driving to save fuel.
	Displays do not really play a role for me when I try to drive energy efficiently.
Technical and mathematical knowledge	I have gained a good technical understanding of fuel-efficient acceleration through specific qualifications or personal activities.
	Concepts such as efficiency and conversion losses are familiar to me.
	I am familiar with integral calculus.
	I often solve mathematical-logical problems in my everyday life.
	Solving mathematical-logical problems does not pose a difficulty to me.

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**Table A2**

*Cross-Level Interactions with Inter-Individual Difference Variables*

No.	Interactions	$\beta$	SE	df	t	p
1	Peak-height*ATI	-0.09	0.03	52.83	-3.04	.004**
2	Peak-duration*ATI	1.72	0.62	52.989	2.79	.007**
3	Peak-duration*peak-height*ATI	-0.03	0.01	152.26	-2.33	.021*
4	Peak-height*experience with consumption displays	-0.03	0.03	48.99	-0.83	.410
5	Peak-duration*experience with consumption displays	0.67	0.64	48.99	1.04	.305
6	Peak-duration*peak-height*experience with consumption displays	-0.02	0.01	170.46	-1.07	.288
7	Peak-height*knowledge	-0.06	0.03	52.83	-1.85	.071
8	Peak-duration*knowledge	1.51	0.65	52.97	2.33	.024*
9	Peak-duration*peak-height*knowledge	-0.03	0.02	168.21	-1.76	.081

*Note.* \*  $p < .05$ , \*\*  $p < .01$ .

## 6. Study 2: Understanding the Knowledge Gaps in Ecodriving: Analysis of Knowledge Accuracy, Uncertainty, and Action Regulation

### 6.1. Abstract

Supporting ecodriving in battery-electric vehicles (BEVs) requires feedback aligned with drivers' mental representations, as effective regulation depends on both know-how (strategies) and know-why (system understanding). When mental representations are inadequate or confidence exceeds actual knowledge, this can undermine performance and feedback processing. This study examined (i) drivers' mental representations of ecodriving via thematic analysis, focusing on knowledge gaps (missing beliefs, situational references, reasoning depth) and references to input-comparator-output information, and (ii) effects of feedback approach on (a) knowledge accuracy, (b) uncertainty due to a lack of knowledge, (c) driving behaviour, and (d) performance.

In a driving simulator study, participants ( $N = 63$ ) drove under one of three conditions: no feedback (G1), real-time consumption trace (G2), or optimal speed recommendation (G3). Afterwards, they provided ecodriving tips and technical explanations, offering insights into their understanding. (i) Qualitative analysis showed broad familiarity with general ecodriving principles (e.g., smooth driving) but little precise or technically grounded guidance. Misconceptions were common, especially on regenerative braking, acceleration, and pedal use. (ii) The feedback approach had: (a) no effect on knowledge accuracy; (b) lower reported uncertainty in G3 vs. G1; (c) selective behavioural effects; (d) no effect on energy consumption. G2 used mechanical braking more and regenerative braking less than G3, while G3 drove slower in constant-speed phases than G1.

Findings indicate that cognitively aligned feedback must go beyond prescribing speed selection or energy raw data. To foster robust ecodriving and reduce uncertainty, systems should support causal understanding and accurate, transferable mental representations.

**Keywords:** Ecodriving, battery electric vehicles, energy efficiency, driving simulation, knowledge

### 6.2. Introduction

Sustainable mobility and energy efficiency are crucial for reducing emissions and optimising resource use in transportation. A key factor in promoting energy-efficient driving behaviour, commonly referred to as ecodriving, is the driver's ability to understand and apply energy-saving strategies of battery-electric vehicles (BEVs) effectively. While external factors such as vehicle technology and infrastructure play a role, driver behaviour significantly impacts actual energy savings (Bingham et al., 2012; Degirmenci & Breitner, 2023; Helmbrecht et al., 2014). This highlights the need to comprehend the cognitive processes behind ecodriving, especially the role of mental representations in action regulation.

Successful ecodriving requires drivers to form a *situational model* (Endsley, 2000) based on mental representations of the relationships between the vehicle, its energy system, and the

driving environment. From a cognitive perspective, ecodriving knowledge can be represented through distinct mental structures with differing assumptions regarding structure, flexibility, and depth of understanding. *Schemas* encode general principles (e.g., neutral gliding is more efficient than regenerative braking; Fiske & Taylor, 1991), *scripts* provide predictable sequences of actions for frequently recurring situations (e.g., anticipatory speed control in stop-and-go traffic; Schank & Abelson, 1975), and *mental models* integrate structural, functional, and causal system understanding (Busselle, 2017; Carroll & Olson, 1988). In the BEV context, *mental models* may reflect drivers' cognitive understanding of ecodriving based on declarative knowledge about energy-efficient strategies (e.g., pressing the driving pedal 30% when accelerating from a standstill), and causal links between behaviour, energy flow, and environmental conditions (e.g., how gradients and air resistance affect braking distance while gliding neutrally). Well-developed mental representations facilitate knowledge retrieval, efficient information processing, flexible adaptation, causal reasoning, and transfer to novel situations, particularly when they are proceduralised through experience and increasing familiarity with BEVs (Bellet et al., 2009; Fiske & Taylor, 1991; Hedge, 2022; Johnson-Laird, 1983; Norman, 1983; Rasmussen, 1983; Seidenstücker & Höger, 2008). Thus, the quality of such representations influences a driver's ability to recognise, evaluate, and execute energy-efficient driving strategies, making them essential for behavioural adaptation and self-regulation.

However, deficits in mental representations can lead to systematic misjudgements, such as the erroneous belief that frequent regenerative braking is inherently efficient, when in fact it is more efficient to minimise situations that require regenerative braking (Franke et al., 2016). Moreover, perceived technical system knowledge (*know-why*) has been shown to predict fuel efficiency (Arend et al., 2019; Franke et al., 2016), indicating that understanding the underlying energy dynamics is just as important as knowing specific ecodriving techniques (*know-how*). This necessitates research focused on conceptualising and enhancing drivers' ecodriving knowledge.

Feedback systems play a critical role in shaping mental representations. From a control theory perspective, behaviour is regulated through feedback loops that acquire information from the vehicle and environment (input), compare actual performance to a desired state (comparator), and prompt behavioural adjustments as output (Carver & Scheier, 1981, 1982; Powers, 1973). Ecodriving feedback approaches provide input (e.g., energy consumption or speed recommendations) that drivers must interpret and act upon. The effectiveness of this process depends on whether feedback supports causal inference and learning or merely prescribes actions. A key distinction among ecodriving feedback approaches lies in the potential to engage in exploratory behaviour, hypothesis formation, or causal reasoning. Recommendation systems offer direct, action-guiding target states (e.g., an optimal speed; Allison et al., 2019), which may

simplify decision-making, reduce cognitive load, and increase action certainty through highly automated information acquisition and analysis. Thus, when trusted and followed, such systems can facilitate optimised pedal control and driving patterns, thereby improving immediate driving performance compared to reliance on a consumption display. At the same time, they may also obscure the reasoning and environmental cues behind the recommendation, thereby impeding system understanding, mental model development, and maintenance and transfer of skills, particularly if the feedback appears opaque, unreliable, or incongruent with expectations (Parasuraman et al., 2000). Conversely, consumption displays typically present raw energy data without explicit guidance (i.e., lower automated information analysis and decision selection). This approach demands active interpretation, causal inference, and hypothesis testing by the driver, which may promote self-directed knowledge acquisition and stronger mental representations but impose greater cognitive demands and ambiguity. Without sufficient knowledge, drivers may struggle to identify meaningful causal patterns, leading to biased or erroneous interpretations (Moll & Franke, 2021). This aligns with broader research on cognitive biases in static driving-related judgments, including misperception of travel time, speed, braking, or consumption (Svenson, 2021). Moreover, studies show that commonly used feedback systems yield limited efficiency gains (Martin et al., 2013), sometimes even resulting in developing inefficient strategies (Arend et al., 2019; Franke et al., 2016).

This reveals a central dilemma: Recommendation systems may reduce uncertainty by directly guiding behaviour and thereby supporting performance, particularly in complex driving situations (Gödker et al., 2025), but they may hinder understanding. Consumption displays, in contrast, demand greater cognitive engagement and may still fail to foster accurate understanding, yet past studies have shown that they can at least provide performance benefits compared to the absence of feedback in simple driving situations (Gödker et al., 2025). To advance ecodriving interventions, it is important to understand not only how accurately drivers can extract knowledge in interaction with these feedback approaches, but also how this knowledge empowers drivers to adapt behaviour and optimise ecodriving performance.

### **Uncertainty Due to a Lack of Knowledge**

Uncertainty plays a crucial role in self-regulation because it may undermine goal pursuit, effort, motivation, resolution of goal conflicts, and effective behavioural control (Light et al., 2018; Pajares & Miller, 1994; Stankov & Lee, 2017; Wolf et al., 2018). It can arise when individuals lack sufficient knowledge to confidently judge strategy effectiveness, select the best behavioural approach, or implement it correctly. In driving, this can manifest as indecision (e.g., “Should I glide neutrally or use regenerative braking now?”), oscillating strategies, or reliance on heuristics, all detrimental to energy efficiency. Affective responses, like frustration, may

further regulate effort positively or negatively depending on the gap between perceived task demands and perceived competence (Carver et al., 2015; Carver & Scheier, 2000; Fuller, 2000, 2005, 2011). For these reasons, uncertainty is an important quality variable in ecodriving research and system evaluation.

When interpreting uncertainty, it is important to consider that higher perceived certainty may or may not align with actual performance, depending on the actual underlying mental representations.

Recommendation systems provide clear action guidance (e.g., optimal pedal position), which can create a strong sense of certainty regarding optimal behaviour. However, this apparent certainty may mask possible knowledge gaps. Drivers may feel confident in following a recommendation, but this does not necessarily align with actual performance. Drivers may feel certain but still drive inefficiently due to inaccurate mental representations that do not empower optimal behavioural control. In this case, high certainty may reduce openness to new information, hindering performance by limiting the ability to refine or update inefficient strategies (Trautwein & Lüdtke, 2007). From a different perspective, drivers feeling too certain in their knowledge may also prioritise their own conclusions over system recommendations (Lee & Moray, 1992; Madhavan & Wiegmann, 2007). In sum, recommendation systems, by providing clear action guidance, may reduce perceived uncertainty and strengthen drivers' sense of competence. However, this perceived certainty does not necessarily reflect actual knowledge (gaps) and can reduce openness to new information. On the other hand, it can also be deduced that intransparent or contradictory recommendations may even expose conflicts with drivers' existing mental representations, thereby increasing uncertainty.

By contrast, consumption displays place greater demands on interpretation and may confront drivers more directly with their knowledge gaps and difficulties in action selection. While this could increase subjective uncertainty due to a lack of knowledge, it may also encourage exploratory behaviour and foster learning. Therefore, understanding how various feedback approaches influence knowledge, behaviour, performance, and uncertainty due to a lack of knowledge is essential for designing ecodriving systems that foster both learning and performance improvements.

### **Understanding Knowledge Gaps**

Against the backdrop of the acknowledged role of mental representations in ecodriving, research has primarily relied on subjective self-reports, think-aloud protocols, or indirect behavioural inferences (Arend et al., 2019; Pampel et al., 2015). These methods, while insightful, have limitations. Subjective ratings are prone to bias, and think-alouds may capture

incomplete verbalisations not fully aligned with driving behaviour (Pampel et al., 2015). Moreover, some conclusions about drivers' *mental models* have been drawn without directly assessing underlying knowledge structures and their accuracy (Pampel et al., 2017). A refined, conceptually grounded measurement of verbalised knowledge accuracy is necessary to explore how knowledge deficits translate into regulation difficulties and uncertainty. Instead of comprehensively assessing distinct constructs of mental representations, the present study focuses on consciously accessible declarative knowledge as a common denominator, crucial for identifying misconceptions that hinder effective regulation and increase uncertainty in decision-making.

Furthermore, ecodriving research rarely links knowledge about how to drive energy-efficiently in various manoeuvres and the underlying technical reasons to actual performance and perceived uncertainty. Evidence from diverse domains shows low correlations between actual knowledge and individuals' experience (McMahon et al., 2020; Radecki & Jaccard, 1995). Such miscalibrations likely affect ecodriving, impairing drivers' capacity for accurate self-regulation and consistent energy-efficient behaviour. Overestimated knowledge reduces the likelihood of seeking new information or updating mental representations, thereby reinforcing suboptimal strategies (Amonhaemanon & Vora-sittha, 2023; Gupta et al., 2014). Hence, examining how feedback influences knowledge accuracy is critical for improving ecodriving support systems.

Building on the assumption that instructing drivers to drive energy-efficiently can make mental representations consciously available (Pampel et al., 2015) and that inexperienced drivers engage in more deliberate reflection due to less routinised behaviour (Rasmussen, 1983), this study examines participants' verbalised ecodriving tips and their technical reasoning as an indicator of their underlying mental representations.

### **6.3. Present Research**

By systematically investigating knowledge (i.e., gaps, references, accuracy), uncertainty, driving behaviour, and performance in different driving manoeuvre prototypes (MPs; e.g., acceleration from a standstill, braking to lower speeds), this study aims to uncover the cognitive mechanisms underlying the interaction with ecodriving feedback approaches. A key objective is to provide empirical insights into how such feedback influences action regulation and how drivers derive action-relevant knowledge (*know-how* and *know-why*) from conventional displays like consumption traces and speed recommendations, thereby laying the groundwork for optimising feedback systems according to actual cognitive needs.

The exploratory research questions are:

- RQ1** What knowledge gaps (i.e., misbeliefs, unconsidered situational demands, and limits in the depth or formulation of explanations) emerge in drivers' verbalised strategies and technical explanations, and how do different feedback approaches impact drivers' verbalised references to different components of action regulation (input, comparator, and output information)?
- RQ2** How do different feedback approaches impact knowledge accuracy for the different MPs?
- RQ3** How do different feedback approaches impact uncertainties due to a lack of knowledge for the different MPs?
- RQ4** How do different feedback approaches impact ecodriving behaviour and performance for the different MPs?

## 6.4. Method

### Participants

A total of 74 participants were recruited after taking part in a separate driving simulator study. Ethics approval for the driving simulator and the follow-up study was granted by the Ethics Committee of the University of Lübeck before the experiment's start (file numbers 2023-680, 2023-680\_1 and 2024-180). Eleven participants were excluded due to missing driving data or non-correctable deviation in the self-generated subject code between the different data sets. The resulting sample included 63 participants between 19 and 38 years old ( $M = 22.4$ ,  $SD = 3.6$ ). Among them, 41 participants (65%) were female, and 15 (24%) had a university degree. The total driving experience across all vehicles was  $M = 37872.0$  km ( $SD = 133767.5$ ). In total, 17 participants (27% of the sample) had driven at least 50 km in a BEV. Their total driving experience with BEVs was  $M = 1388.7$  km ( $SD = 2408.1$ ). A further 11 participants (17%) reported experience with (plug-in) hybrid electric vehicles. Regarding the Affinity for Technology Interaction (ATI), the sample showed a wide range (ranging from 1.1 to 6.0), with a mean score of 3.9 ( $SD = 1.2$ ), slightly higher than the values reported for the general population ( $M = 3.61$ ;  $SD = 1.08$ ; Franke, Attig, et al., 2019).

### Procedure

Participants first took part in a driving simulator experiment. They were randomly assigned to one of three groups: no information while driving (*control*), a consumption trace (*consumption trace*), or a recommendation of optimal energy-efficient speed (*speed recommendation*). Before

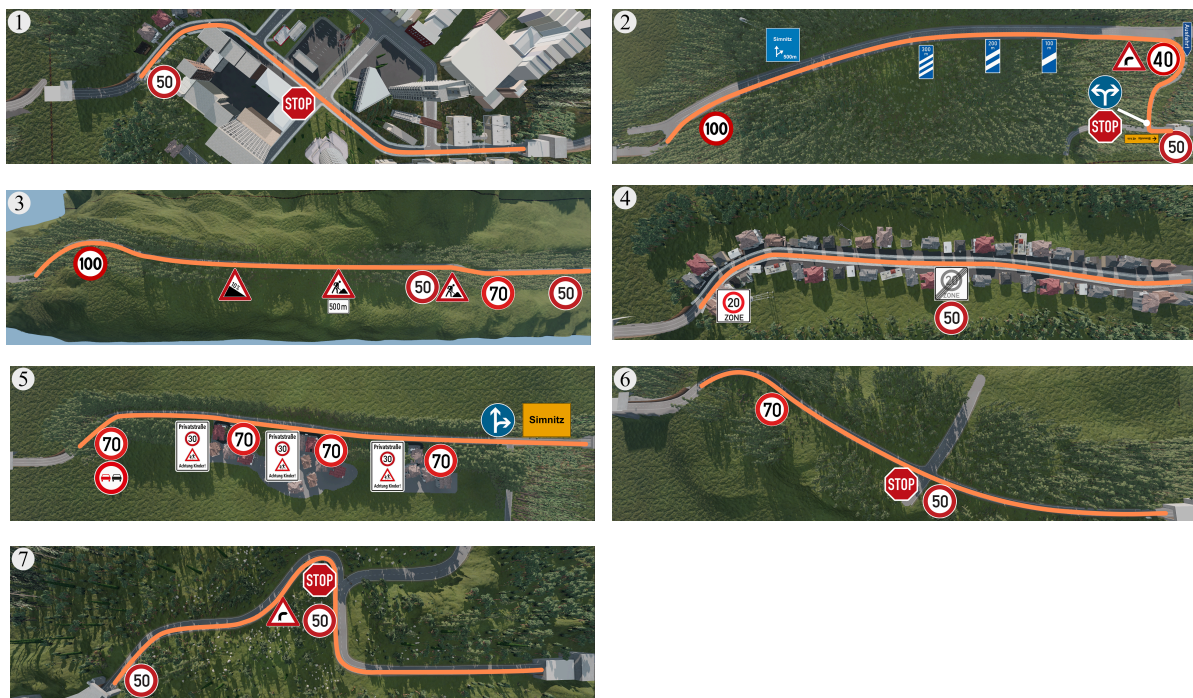
driving, participants provided informed consent. Throughout the experiment, participants were provided with basic instructions explaining the driving simulator, the experimental procedure, the experiment rules, and their tasks. The latter included driving energy-efficiently, adhering to traffic regulations, and following road signs to the fictional city of *Simnitz* to avoid navigational errors. Additionally, participants were instructed to reach the destination of each driving sector within a predefined time limit, which was based on the estimated travel time of a driver maintaining approximately 90% of the speed limit and to respond to online prompts whenever they entered a tunnel.

Initially, participants indicated their driving experience and assessed their perceived ecodriving and technical background knowledge. Before the actual experiment, participants familiarised themselves with the driving simulation and the experiment rules during a 4-minute acclimatisation drive that included various manoeuvres, speed limits, curves, and hills. This was followed by the experiment's baseline and experimental block, each comprising two test drives and two sub-blocks. Across both blocks, seven driving sectors were completed (see Figure 1). These sectors were grouped into two sub-blocks based on complexity, each containing three to four sectors. The order of the sub-blocks and the sequence of sectors within each sub-block were randomised. In the experimental block, the corresponding feedback approaches were available to participants in the experimental groups. During and after all blocks, participants completed several interim questionnaires on the laptop that were not considered in the present analyses. Finally, they were asked to provide sociodemographic information.

Participants could participate in a follow-up study after participating in the driving simulator study. Since participation was voluntary, the final group sizes were unfortunately not balanced ( $n_{control} = 25$ ,  $n_{consumption} = 15$ ,  $n_{recommendation} = 23$ ). Participants were asked to give tips on various MPs and evaluate their perceived uncertainty due to a lack of knowledge, resulting in difficulties driving energy-efficiently. The entire procedure, including the driving simulator experiment and the follow-up study, took approximately 107 minutes per participant.

**Figure 1**

*Main Driving Sectors*



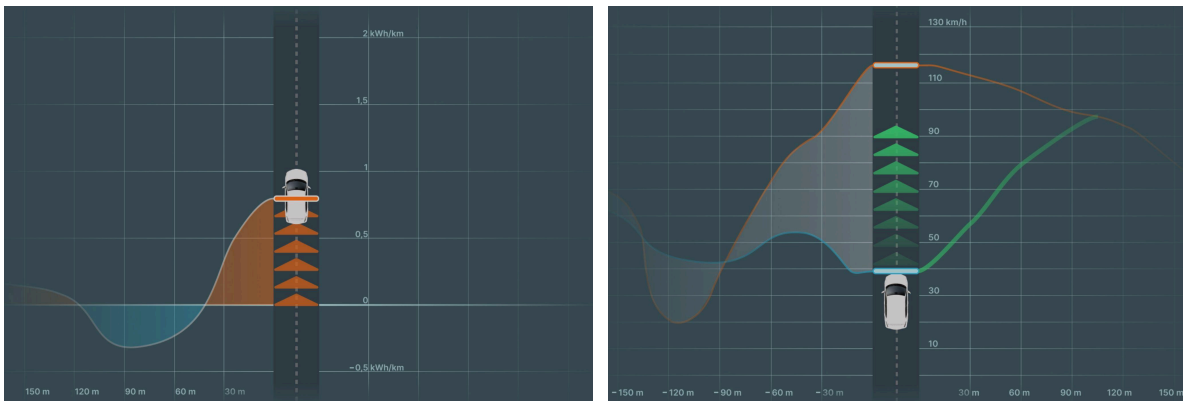
### **BEV Driving Simulator and Feedback Approaches**

The study was conducted in the EcoSimLab driving simulator at the Institute of Multimedia and Interactive Systems of the University of Lübeck, using a simulated Renault Zoe EV and the EcoDrivingTestPark as the driving environment (Gödker et al., 2024). The hardware setup consisted of three 55" 120 Hz monitors, providing a 180° field of view, and a Fanatec gaming simulation rig that included a seat, wheelbase, and pedals. A compact steering wheel, modelled after the Renault Zoe, was mounted to enhance realism, and both the wheel and pedals featured force feedback. The simulation software used was BeamNG.tech, a variant of the BeamNG.drive simulation platform (BeamNG GmbH, 2022).

Two different ecodriving feedback approaches were implemented and presented on a 10.5" Samsung Galaxy S4 tablet mounted below the simulation monitors, right of the steering wheel (see Figure 2). The *speed recommendation* display provided a precomputed optimal velocity profile based on a dynamic programming optimisation that incorporated road curvature, speed limits, stop signs, road gradient and a realistic vehicle model of a Renault ZOE Q90 (Gödker et al., 2024, 2025; Heidinger et al., 2023).

**Figure 2**

*Consumption Trace (left) and Speed Recommendation (right) Displays*



This method ensured that each local driving decision aligned with a global energy-minimisation objective, creating a predefined optimal speed trajectory. The *speed recommendation* display compares this optimal speed with the driver's actual speed over the previous and upcoming 150 meters, offering real-time feedback on deviations from the most energy-efficient speed. Additionally, an action cue in the form of green arrows indicated the recommended speed 50 meters ahead, further guiding drivers toward efficient driving behaviour.

The second feedback approach, the *consumption trace* display, visualised instantaneous energy consumption (kWh/100 km) over the past 150 meters. This real-time feedback allowed drivers to reflect on their past manoeuvres and adjust their strategy accordingly. Both displays updated at 10 Hz, ensuring periodic prompts to encourage adherence to the optimal driving strategy.

### Scales and Measures

According to common practice (e.g., Cripps, 2017), Cronbach's alpha was interpreted as poor ( $.5 \leq \alpha < .6$ ), questionable ( $.6 \leq \alpha < .7$ ), acceptable ( $.7 \leq \alpha < .8$ ), good ( $.8 \leq \alpha < .9$ ), or excellent ( $\alpha \geq .9$ ) for all measures. Scales contained a 6-point Likert scale ranging from 1 (completely disagree) to 6 (completely agree), if not otherwise stated.

#### *Perceived Uncertainty Due to a Lack of Knowledge*

Participants were instructed to indicate to what extent they feel uncertain about driving as energy-efficient as possible due to a lack of knowledge. Specifically, it was explained that this uncertainty may arise from (a) not knowing the most energy-efficient driving strategies, (b)

difficulties in knowing how and when to implement a specific behaviour, or (c) not understanding why a behaviour is energy-efficient. The construct was assessed with five items referring to the different MPs: *stopping* (e.g., at traffic lights or stop signs), *braking to lower speeds* (e.g., from 50 km/h to 30 km/h), *accelerating from a standstill*, *accelerating to higher speeds* (e.g., 50 km/h to 100 km/h) and *constant driving*. One example item is: "I was uncertain about driving as energy-efficiently as possible due to a lack of knowledge when accelerating to higher speeds." The scale's internal consistency was acceptable ( $\alpha = .79$ ;  $M = 3.5$ ,  $SD = 1.0$ ).

### *Qualitative Tip Data*

Participants were asked to formulate tips on how to drive as energy-efficiently as possible in different MPs. They were asked to describe them in complete sentences as specifically as possible: (1) what information from the vehicle or the environment needs to be paid attention to (input), (2) what needs to be done with the vehicle controls like the driving pedal, brake pedal, and steering wheel (output) and (3) how to immediately check that the behaviour is successful (comparator). To do this, they were asked to imagine that they were a passenger in an electric vehicle, the route was familiar, and the weather was sunny and calm at 20 °C. It was assumed that the actual driver was motivated to drive energy-efficiently.

Participants were also asked to provide technical reasons why the tips they gave optimise energy efficiency, as there is evidence that technical explanations of behavioural strategies are key to increasing energy efficiency (Arend et al., 2019; Sureth et al., 2019). We analysed the qualitative data manoeuvre-specific based on *Thematic Analysis* (Braun & Clarke, 2006). After familiarisation with the data, an initial coding phase was conducted that yielded an extensive list of codes (e.g., aspects of vehicle behaviour, types of interaction with vehicle control, specifications of pedal use, references to environmental or vehicle information, and patterns of formulation) for each MP. During this phase, first ideas for possible overarching themes (i.e., thematic clusters) were noted (e.g., different ways of varying pedal interactions over time). In a subsequent step, related codes were grouped into preliminary themes. The analysis was carried out on a semantic level (Braun & Clarke, 2006), focusing on concrete behaviours and articulated beliefs, and maintaining a relatively low level of abstraction. For the domain of missing beliefs, themes were additionally informed by the ideal reference responses, in order to capture both false and absent elements of participants' knowledge. In the final phase, participants' statements were coded with respect to the refined thematic framework. Minor revisions and refinements of the themes were conducted during this process, also ensuring consistency between the MPs.

### *Mean Proportions of Tip References to Input, Comparator, and Output*

Participants' tips were coded for the presence of input, comparator, and output information. A liberal coding approach was used due to many responses' predominantly nonspecific or generic phrasing. If a statement included information about how to execute the behaviour, even without explicitly mentioning pedal interaction, output information was coded as 1. For instance, "Slowly approach the line and continuously reduce your speed" was considered sufficient and thus coded as output = 1. In contrast, statements like "brake" were deemed too vague and coded as 0. Analogous criteria were applied for input and comparator information. Statements that were overly general or did not clearly reference relevant aspects were coded as 0 (e.g., "Just consider if respective aspects exist"). More specific descriptions were coded as 1, such as "I monitor how far the stop sign is and where I need to stop."

For each participant, mean scores were calculated across all MPs for input, comparator, and output information. These values represent the relative proportion of tips that included each respective information and thus indicate the extent to which the respective aspect was addressed in the participants' verbalisations.

### *Knowledge Accuracy*

Strategy knowledge must be correct and precise to implement the most energy-efficient driving behaviour. Thus, these aspects are evaluated from 0 = "completely incorrect/imprecise" to 2 = "completely correct/precise" for each MP and both knowledge forms (*know-how* and *know-why*). The manoeuvre-specific knowledge accuracy is the sum of these four values, ranging from 0 = "completely inaccurate" to 8 = "completely accurate." Thus, completely accurate manoeuvre strategy knowledge has the maximum possible precision and correctness in *know-how* and *know-why*.

We applied an automated natural language processing tool (GPT-4o-mini; OpenAI, n.d.) to systematically code qualitative driving tips (*know-how*) and their technical explanations (*know-why*). Using manoeuvre-specific structured prompts, the tool evaluated correctness and precision against predefined ideal reference responses, which were carefully and systematically generated by experts (detailed generation process see Appendix A; final output see Table 1). Each ideal reference response was supplemented by two alternative formulations per coding category (correct, moderately correct, incorrect; precise, moderately precise, imprecise) to capture natural variation in phrasing. For example, formulations such as "Accelerate below 60 km/h with a constant pedal position of around 30%" and similar variants like "Press the accelerator pedal constantly by about a third so that you accelerate moderately" were both coded as entirely correct.

## Study 2: Understanding the Knowledge Gaps

**Table 1**

*Ideal Reference Responses and Behavioural Driving Metrics for Five Driving Manoeuvre Prototypes*

MP	Know-how	Know-why	Behavioural driving metrics
1. Acceleration from standstill	Accelerate below 60 km/h with a constant pedal position of around 30%.	This will allow you to move through the motor's efficiency ranges as optimally as possible to optimise the ratio of speed gain to energy consumption.	<ul style="list-style-type: none"> <li>• Median throttle position</li> <li>• Median acceleration (m/s<sup>2</sup>)</li> </ul>
2. Acceleration to higher speeds	Accelerate over 60 km/h with a constant pedal position of around 40%.	This will allow you to move through the motor's efficiency ranges as optimally as possible to optimise the ratio of speed gain to energy consumption.	<ul style="list-style-type: none"> <li>• Median throttle position</li> <li>• Median acceleration (m/s<sup>2</sup>)</li> </ul>
3. Braking to lower speeds	When braking, you should glide neutrally as much as possible by only touching the accelerator pedal to such an extent that energy is neither consumed nor recovered. If this is not enough, use regenerative braking slightly by releasing the pedals.	This way, you optimally use the kinetic energy built up for propulsion and avoid conversion losses during regenerative braking.	<ul style="list-style-type: none"> <li>• Proportions of neutral gliding, regenerative braking, and mechanical braking (%)</li> <li>• Median acceleration (m/s<sup>2</sup>)</li> </ul>
4. Stopping	If possible, brake by neutral gliding by pressing the accelerator pedal 1%. If this is not sufficient, use regenerative braking slightly by releasing the pedals. If light regenerative braking is insufficient, press the brake pedal - but not too hard so as not to brake mechanically. To stop properly, press the brake pedal from walking speed.	Neutral gliding, if possible, avoids conversion losses during regenerative braking. Pressing harder on the brake pedal activates the mechanical brake in addition to regenerative braking. As a result, the momentum energy is ultimately converted into heat and is, therefore, completely lost. This way, you avoid mechanical braking, and at least some energy is recovered. Neutral gliding, if possible, avoids conversion losses during regenerative braking.	<ul style="list-style-type: none"> <li>• Proportions of neutral gliding, regenerative braking, and mechanical braking (%)</li> <li>• Median acceleration (m/s<sup>2</sup>)</li> </ul>
5. Constant driving	Drive at a constant speed as far as possible by driving with foresight so that you neither accelerate unnecessarily nor 'brake away' your built-up speed (momentum). If you are driving on roads with a speed limit of 60 km/h or higher, keep your speed as low as possible.	Every acceleration (build-up of momentum) costs energy. You can therefore save energy by avoiding the build-up of kinetic energy that is not needed. When you reduce speed, previously accumulated kinetic energy (momentum) is lost. In addition, at high speeds, air resistance mainly determines energy consumption, as this increases quadratically - i.e. disproportionately - with speed. This leads to significant energy losses.	<ul style="list-style-type: none"> <li>• Mean velocity (km/h)</li> <li>• Mean velocity difference to optimal speed (km/h)</li> </ul>

*Note.* The ideal reference responses are valid for the given energy model (Zoe Q90). MP = Manoeuvre prototype.

The coding process was iterative: initial prompts and scoring thresholds were refined based on discrepancies identified by comparing the tool's outputs with human evaluations on a manually reviewed subset. This subset included up to five randomly selected, manoeuvre-specific

examples per coding category (correctness/precision = {0;1;2}) for both tips and technical explanations, amounting to checks of 50-52 examples, respectively. Then, the prompts were adjusted to ensure consistent coding of closely related formulations, reducing AI coding inconsistencies. Finally, interrater reliability between AI and a human coder was excellent, with Cohen's kappa  $\kappa = 0.85$ , indicating almost perfect agreement (Landis & Koch, 1977). The final coded dataset, containing the checked scores and justifications for 315 tips and 315 technical explanations, was subsequently prepared for statistical analysis, interpretation, and visualisation.

### *Driving Data*

Exploratory analysis revealed numerous speed violations and inconsistent data in Sectors 4 and 5 due to rapid or artificial speed limit changes (i.e., suboptimal design). Sector 6 was also excluded as it was less energy-relevant, showing limited variation in consumption-related dynamics, low group variability, and smaller mean differences. Moreover, its uphill acceleration phases distorted optimal throttle positions, biasing acceleration analysis. Thus, Sectors 4–6 were excluded. For the remaining sectors, individual values were first z-standardised per metric (independent of phase or group) and then averaged across sectors. We analyse key metrics for each MP to assess driver behaviour and performance. Representative behavioural metrics were selected based on their relevance (see Table 1).

Two metrics are used for [MP1] *acceleration from standstill* and [MP2] *acceleration to higher speeds*. Median throttle position captures driver input while filtering out extremes, providing a stable indicator of acceleration behaviour. Median longitudinal acceleration ( $\text{m/s}^2$ ) complements this by measuring the actual force applied during acceleration.

For [MP3] *braking to lower speeds* and [MP4] *stopping*, three behavioural indicators are examined. The neutral gliding and regenerative braking proportions capture the potential for energy-saving. In contrast, the proportion of mechanical braking indicates reliance on conventional braking, where kinetic energy is lost as heat. Median longitudinal acceleration ( $\text{m/s}^2$ ) reflects the intensity of braking.

[MP5] *Constant driving* is best characterised by speed stability, and minimal energy fluctuation, making velocity-based metrics most relevant. Mean velocity (km/h) reflects the typical driving speed, incorporating all variations. The median would obscure meaningful dynamics. The mean deviation from optimal velocity (km/h) indicates systematic over- or under-speeding. Negative values reflect speeds below the energy-optimal speed; positive values indicate excessive speeds.

In addition to behavioural metrics, mean energy consumption (Wh) is assessed for each MP. Unlike total energy consumption, which is highly dependent on manoeuvre length and thus unsuitable for comparison, mean energy consumption offers a more accurate and standardised measure of energy efficiency across participants and manoeuvres. Individual variations in driving behaviour often result in different durations or distances for the same manoeuvre, making total values misleading. Distance-based metrics such as Wh/100 km pose further issues: short, high-energy manoeuvres can yield disproportionately high values, while longer, less intense ones may appear artificially efficient. This distorts aggregation and hinders meaningful comparison. By contrast, mean energy consumption (Wh) is independent of distance, enabling more robust and equitable evaluation across varying executions.

To derive the manoeuvre-specific metrics, driving data were grouped by participant and sector. Dynamic manoeuvre detection segmented the continuous signal into behavioural phases. A low-pass filter reduced speed signal noise, allowing more reliable acceleration estimates via temporal differentiation. Based on the resulting acceleration profile, along with energy consumption and engagement of the hydraulic brake, each data point was initially classified into fine-grained manoeuvre states: standing, constant driving, acceleration, regenerative braking, neutral deceleration, mechanical deceleration, and deceleration with braking. A state machine refined these sequences to ensure temporal consistency and remove implausible transitions. Finally, states were aggregated into the higher-level manoeuvre types [MP1] *acceleration from standstill*, [MP2] *acceleration to higher speeds*, [MP3] *braking to lower speeds*, [MP4] *stopping*, and [MP5] *constant driving*.

## 6.5. Results

For all analyses, the threshold of  $\alpha$  was set to .05, and effect sizes were interpreted according to Bühner (2021), Field et al. (2012) and Cohen (1988, 1992). Small effects were defined as  $\eta^2 = \epsilon^2 = .01$ ,  $V = r = 0.10$ , and  $d = 0.20$ ; moderate effects as  $\eta^2 = \epsilon^2 = .06$ ,  $V = r = 0.30$ , and  $d = 0.50$ ; and large effects as  $\eta^2 = \epsilon^2 = .14$ ,  $V = r = 0.50$ , and  $d = 0.80$ . The analyses were performed in R (R Core Team, 2024) using RStudio (Posit Team, 2025).

Statistical assumptions for the applied parametric tests were evaluated prior to analysis. Normality of residuals and variance homogeneity were checked with the Shapiro–Wilk test (Shapiro & Wilk, 1965) and Levene’s test (Levene, 1960). In case of violated assumptions of the ANOVA, Kruskal–Wallis tests (Kruskal & Wallis, 1952) or Welch’s ANOVAs (Welch, 1951) were conducted for metric variables and Pearson’s chi-square test (Agresti, 2007; Pearson, 1900) for categorical variables (gender, education).

No significant group differences were observed for total driving experience (km), BEV driving experience (km), age, gender, education, ecodriving motivation (eight items adapted from previous work of the research group and Arend & Franke, 2017), ecodriving knowledge and technical knowledge (five and four items based on previous work of the research group and Arend et al., 2019; Arend & Franke, 2017), or affinity for technology interaction (Franke, Attig, et al., 2019),  $ps < .05$ . The groups can thus be considered comparable (see Table B1 in Appendix B).

### **Knowledge Gaps (RQ1)**

#### *Thematic Analysis*

To explore drivers' false and missing beliefs regarding energy-efficient driving with BEVs, we conducted a *Thematic Analysis* (Braun & Clarke, 2006) of participants' qualitative responses across the five MPs (see Tables C1 and C2 in Appendix C). The results reveal several recurring misconceptions and incomplete mental representations, both across and within specific driving contexts. Given the complexity of the findings, the overarching insights are summarised below.

**Lack of references to key efficiency factors.** Overall, participants rarely, if ever, referred to core efficiency aspects such as neutral gliding, efficiency maps, or aerodynamic drag. None of the participants mentioned neutral gliding or aerodynamic drag when discussing stopping, braking, or constant-speed driving. Additionally, nearly all participants (97%–98%) failed to refer to conversion efficiency in their acceleration tips. Approximately one-third of the participants (30%–32%) made no specific reference to acceleration intensity as they formulated behaviour to be avoided only in abstract terms (e.g., avoid full-throttle) or did not specify any acceleration intensity at all.

**Acceleration intensity is misrepresented.** Only two participants (3%) correctly recommended moderate acceleration as the most energy-efficient. Almost half of the participants assumed that (very) slow acceleration is most energy-efficient (48%–54%), while a smaller proportion advocated for rapid acceleration (8%). Although a substantial proportion (37%–38%) emphasised maintaining a constant acceleration, isolated misconceptions also emerged, for example, equating acceleration behaviour across different speed ranges or recommending varying pedal pressure or acceleration intensity over time (2% in each case).

**Misunderstandings regarding regenerative braking and coasting.** Several participants misinterpreted BEV regenerative braking. Some conflated regenerative braking with coasting (8%–11%), while others incorrectly believed braking consumes energy (up to 8%). Additionally, 11%–14% of participants explicitly recommended the preferential use of regenerative braking.

However, participants mostly used the terms regenerative braking and coasting without clear definitions. This lack of conceptual clarity is particularly relevant given the central role of these processes in electric vehicle dynamics. Isolated responses even reflected counterproductive beliefs, such as the notion that hard braking minimises energy loss or that regenerative braking is more efficient than coasting. Nearly one-third of participants also appeared uncertain about the relationship between pedal interaction and vehicle behaviour. For instance, 21%–27% of participants assumed that releasing the accelerator pedal results in coasting (“rolling out”), although the vehicle is actually regenerative braking in this case. Thus, participants’ understanding of when and how regenerative braking is activated was often unclear. They never differentiated between varying intensities of regenerative braking and rarely among braking strategies in general. One strategy (either coasting, regenerative or mechanical braking) was often emphasised exclusively, without reference to situational or vehicle-specific factors.

**Simplification regarding constant driving.** While most participants correctly recommended maintaining a constant speed, a notable proportion (32%) falsely referred to the use of cruise control, often without further explanation. Furthermore, opinions diverged on whether maintaining a constant speed (43%) or a constant pedal position (21%) is appropriate. In this context, three participants (5%) incorrectly assumed that keeping the accelerator pedal in a fixed position consistently results in a constant speed. Although coasting was rarely mentioned explicitly, one participant (2%) expressed the misconception that pulse-and-glide driving is less efficient than maintaining a constant speed.

**Vague or absent pedal strategies.** Descriptions of pedal interaction were frequently missing or too vague. Depending on the MPs, between 22% and 64% of participants did not specify any pedal interaction. Acceleration manoeuvres showed the lowest level of specificity (49%–64%), followed by constant speed (32%) and braking manoeuvres (22%–25%). Interaction with the accelerator pedal was explicitly described more frequently (37%–64%) than with the brake pedal (2%–24%). While accelerator pedal interaction was typically either explicitly stated or entirely omitted, descriptions of brake pedal interaction were more often paraphrased implicitly (16%–38%).

**Use of external information and anticipatory behaviour.** Overall, references to external information related to the vehicle (e.g., speedometer, consumption display, sound) or the environment (e.g., terrain, traffic signs) were relatively rare. Among these, traffic signs and signals were mentioned most frequently (6%–41%), followed by vehicle-related cues (11%–21%), while target speed (0%–11%), traffic (0%–3%), and slope or road layout (5%–18%) were mentioned less often. When referencing vehicle information, it was often vague—for example, “because the display showed it”—and lacked integration into broader driving strategies. This suggests a missed opportunity to use real-time feedback to support

energy-aware behaviour. At the level of specific MPs, most references occurred in the context of braking manoeuvres, except for avoiding speed fluctuations. However, not a single reference was made to the target speed within the braking MPs. Interestingly, 73% of participants emphasised avoiding speed fluctuations during constant-speed driving, suggesting an implicit awareness of general energy efficiency principles.

**Generic formulations and absent reasoning patterns.** Participants frequently relied on abstract or avoidance-based behavioural formulations without linking them to underlying energy principles. Rather than explicitly stating what should be done, many participants described what should be avoided—for example, “don’t go full throttle,” “not too abrupt,” or “don’t push it all the way.” These formulations reflect a general awareness of inefficient behaviour but provide little constructive guidance on how to act efficiently.

Although generic energy-related goals such as “less consumption” were common (29%–64%), they were often not accompanied by substantive explanations. Notably, a large proportion of participants (up to 44%) did not provide any specific energy-related reasoning. Even when technical terms such as “regenerative braking” were mentioned, they were rarely embedded in more elaborate justifications (29% generic references to regenerative braking). Finally, there were isolated but explicit references (2%–8%) to concepts transferred from ICEVs across all MPs—for example, assumptions about clutch behaviour or gear usage.

**Summary.** Participants generally demonstrated familiarity with the basic principles of ecodriving. They frequently identified relevant behaviours such as gentle braking, steady and smooth driving, and avoiding aggressive acceleration. For example, only one participant precisely suggested pressing the accelerator pedal to one-third until reaching the desired speed. These vague formulations reflect a general awareness of inefficient behaviour but provide little constructive guidance on how to drive efficiently.

However, their ability to justify these behaviours using technical or vehicle-specific reasoning was limited. Key concepts, such as neutral gliding, efficiency ranges, and the aerodynamic impact of high speeds, were rarely mentioned and often misunderstood.

Several misconceptions emerged, including incorrect assumptions about optimal acceleration intensity, misunderstandings regarding regenerative braking and coasting, and inaccurate beliefs about the relationship between pedal interaction and vehicle behaviour.

#### *References to Input, Comparator, and Output*

Although participants were explicitly asked to refer to input, comparator and output, their tips did not include all these aspects. Likewise, the tips were not always formulated in complete

sentences as instructed. 87% of drivers' tips included information on what to do with the vehicle controls (output). Information on how to check the success of their behaviour (comparator) was only given by an average of 16% of people. In addition, 36% of people referred to what information about the vehicle or the environment should be paid attention to (input).

A Kruskal–Wallis test on the mean proportion of input references revealed a statistically significant effect (see Table 2). Regarding the mean proportion of comparator references and the mean proportion of output references, the group had no significant effects ( $p = .125$  and  $p = .601$ ).

**Table 2**

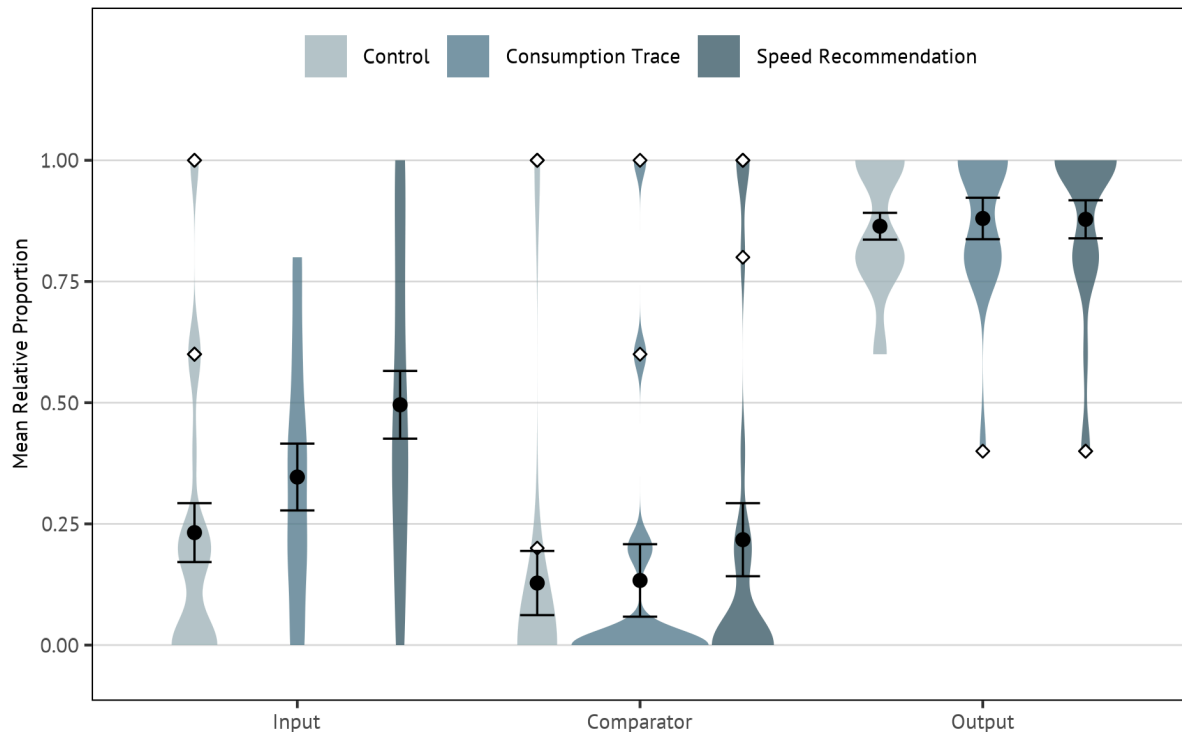
*Nonparametric Test Statistics and Post Hoc Comparisons for the Input, Comparator, and Output References*

Variable	$H(2)$	$p$	$\epsilon^2$	Dunn's post hoc test	Statistic	$p_{adj}$	$r$
Input	8.96	.011	.14	Control - consumption trace	1.40	.212	.22
				Control - speed recommendation	3.01	<.001	.43
				Consumption trace - speed recommendation	1.25	.212	.20
Comparator	2.63	.269	.04				
Output	0.85	.652	.01				

Dunn's post-hoc tests with Benjamin–Hochberg correction indicated that the *speed recommendation* group ( $M = 49.6\%$ ,  $SD = 33.5$ ) had a significant higher mean proportion of input reference than the control group ( $M = 23.2\%$ ,  $SD = 30.4$ ),  $p = .008$ ,  $r = .43$ . There were no significant differences between the consumption trace group ( $M = 34.7\%$ ,  $SD = 26.7$ ) and both the control group ( $p = .222$ ,  $r = -.23$ ) and the speed recommendation group ( $p = .239$ ,  $r = .19$ ). Group-specific mean proportions are visualised in Figure 3.

**Figure 3**

Mean Proportions of Input, Comparator, and Output References Across Driving Manoeuvre Prototypes (N = 63)



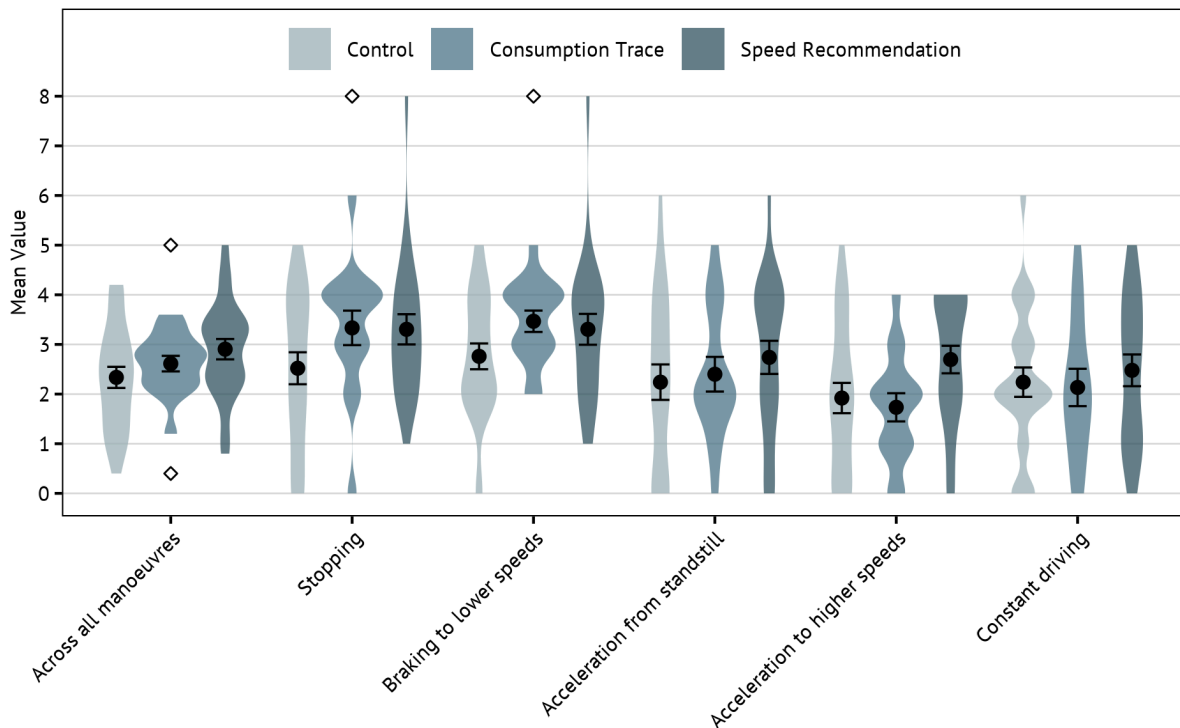
Note. The plot includes means (black dots), standard errors (vertical lines), and outliers (white diamonds), defined as values more than  $1.5 \times \text{IQR}$  below  $Q_1$  or above  $Q_3$ .

### Knowledge Accuracy (RQ2)

Five Kruskal–Wallis tests and one ANOVA were applied to examine the effect of groups on knowledge accuracy for various MPs (see Table D1 in Appendix D). No significant group differences existed within and across the MPs,  $p_s > .05$ . As visualised in Figure 4, knowledge accuracy was low across groups and MPs ( $M = 2.6$ ,  $SD = 1.0$ ), with the lowest accuracy observed for [MP2] *acceleration to higher speeds* ( $M = 2.2$ ,  $SD = 1.4$ ) and the highest for [MP3] *braking to lower speeds* ( $M = 3.1$ ,  $SD = 1.3$ ). Knowledge accuracies for [MP5] *constant driving* ( $M = 2.3$ ,  $SD = 1.5$ ), [MP1] *acceleration from standstill* ( $M = 2.5$ ,  $SD = 1.6$ ), and [MP4] *stopping* ( $M = 3.0$ ,  $SD = 1.5$ ) fell between those manoeuvres.

Figure 4

Knowledge Accuracy Across and Within Different Driving Manoeuvre Prototypes (N = 63)



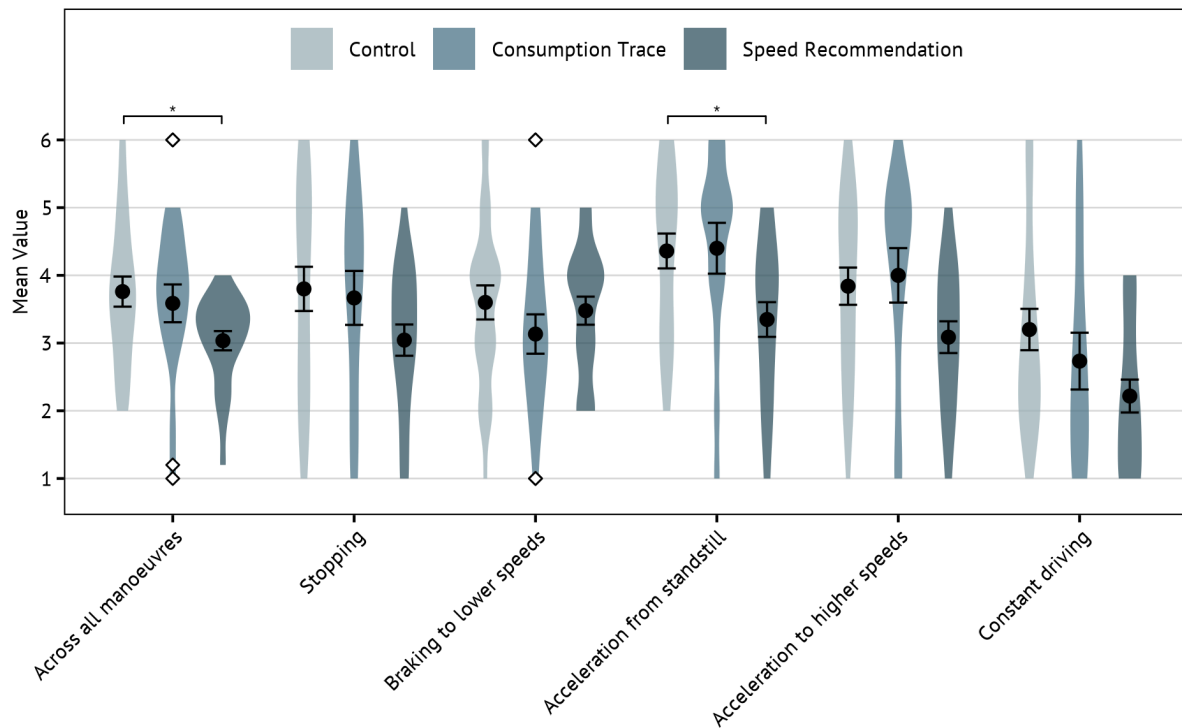
Note. The plot includes means (black dots), standard errors (vertical lines), and outliers (white diamonds), defined as values more than  $1.5 \times \text{IQR}$  below  $Q_1$  or above  $Q_3$ .

### Uncertainty Due to a Lack of Knowledge (RQ3)

A Welch's ANOVA was conducted due to unequal variances and unbalanced group sizes to examine differences in uncertainty ratings between the groups. The results revealed a significant difference among the groups,  $F(2, 32.52) = 4.32, p = .022$ , with a moderate effect size ( $\eta^2 = .11$ ). The descriptive statistics indicate that the *speed recommendation* group reported the lowest uncertainty ratings ( $M = 3.0, SD = 0.7$ ), while the *control* group had the highest ratings ( $M = 3.8, SD = 1.1$ ). The *consumption trace* group fell in between ( $M = 3.6, SD = 1.1$ ). Games-Howell post-hoc tests were performed to investigate group differences further. The pairwise comparisons showed that there was only a significant difference between the *speed recommendation* group and the *control* group ( $p = .024, d = 0.79$ ; medium to large effect), with the *speed recommendation* group reporting lower uncertainty due to a lack of knowledge than the *control* group (see Figure 5).

Figure 5

Uncertainty Due to a Lack of Knowledge Across and Within Driving Manoeuvre Prototypes (N = 63)



Note. The plot includes means (black dots), standard errors (vertical lines), and outliers (white diamonds), defined as values more than  $1.5 \times \text{IQR}$  below  $Q_1$  or above  $Q_3$ . \*  $p < .05$ .

Additionally, five Welch's ANOVA were calculated to test the effect of group on uncertainty due to a lack of knowledge within the MPs. There was a significant group difference for [MP1] *acceleration from standstill* ( $p = .016$ ,  $\eta^2 = .13$ ). While group differences in [MP5] *constant driving* and [MP2] *acceleration to higher speeds* approached significance, they were non-significant,  $p = .056$  and  $p = .062$ . All other MPs also did not show significant group effects. A Games-Howell post-hoc test was performed to further investigate group differences regarding [MP1] *acceleration from standstill*. The pairwise comparisons showed that there was only a significant difference between the *speed recommendation* and the *control* group ( $p = .021$ ,  $d = 0.80$ ; large effect), with the *speed recommendation* group reporting lower uncertainty due to a lack of knowledge ( $M = 3.3$ ,  $SD = 1.2$ ) than the *control* group ( $M = 4.4$ ,  $SD = 1.3$ ). Group-specific mean values per MP are visualised in Figure 5.

**Driving Behaviour and Performance (RQ4)**

Multiple Welch's ANOVAs were conducted (see Table 3) to examine group differences for each manoeuvre, followed by Games–Howell post-hoc comparisons. As a randomisation check, we first checked whether significant group differences existed in the pre-trial. This was not the case with  $ps > .05$ . Thus, the post-trial values could be further analysed concerning group differences. Descriptive statistics of the non-standardised values are reported in Table D2 in Appendix D.

**Table 3***Inferential Statistics of Driving Performance*

MP	Metric	<i>F</i>	df1	df2	<i>p</i>	$\eta^2$
1. Acceleration from standstill	<b>Mean consumption (kWh)</b>	0.27	2	31.54	.762	.02
	Median of throttle position	1.22	2	36.39	.308	.06
	Median of acceleration (m/s <sup>2</sup> )	0.16	2	34.49	.849	.01
2. Acceleration to higher speeds	<b>Mean consumption (kWh)</b>	0.05	2	32.78	.953	<.01
	Median of throttle position	0.24	2	35.61	.790	.01
	Median of acceleration (m/s <sup>2</sup> )	0.48	2	32.29	.623	.03
3. Braking to lower speeds	<b>Mean consumption (kWh)</b>	0.06	2	35.50	.940	<.01
	Neutral gliding (proportion)	0.01	2	36.09	.990	<.01
	Regenerative braking (proportion)	5.84	2	35.98	.006	.25
	Mechanical (proportion)	9.38	2	34.21	.001	.35
	Median of acceleration (m/s <sup>2</sup> )	3.23	2	32.79	.052	.16
4. Stopping	<b>Mean consumption (kWh)</b>	0.71	2	29.50	.501	.05
	Neutral gliding (proportion)	0.30	2	30.04	.741	.02
	Regenerative braking (proportion)	2.22	2	28.38	.127	.14
	Mechanical (proportion)	1.09	2	28.46	.348	.07
	Median of acceleration (m/s <sup>2</sup> )	0.32	2	33.79	.730	.02
5. Constant driving	<b>Mean consumption (kWh)</b>	1.29	2	31.75	.290	.07
	Mean velocity (km/h)	3.99	2	38.60	.027	.17
	Mean velocity-optimum difference (km/h)	5.20	2	37.37	.010	.22

There were no significant group differences in the manoeuvres [MP4] *stopping*, [MP1] *acceleration from standstill*, and [MP2] *acceleration to higher speeds* in all cases ( $ps > .05$ ) with  $\eta^2$  ranging from  $< 0.01$  to  $0.14$  (small to large).

In the manoeuvre [MP3] *braking to lower speeds*, there were significant group differences regarding the proportion of regenerative braking and the proportion of mechanical braking (large effect). Games–Howell post-hoc tests revealed significant differences in the proportion of mechanical braking between the *control* group and the *consumption trace* group as well as the *consumption trace* group and the *speed recommendation* group,  $t(29.87) = 2.79, p = .024, d = 0.93$  (large effect) and  $t(27.84) = 4.37, p < .001, d = 1.48$  (large effect). The *consumption trace* group ( $M = 15.7\%$ ,  $SD = 4.2$ ) had a significantly higher use of mechanical braking than the *control* group ( $M = 11.4\%$ ,  $SD = 4.7$ ) and the *speed recommendation* group ( $M = 9.1\%$ ,  $SD = 4.3$ ). Furthermore, the *consumption trace* group ( $M = 70.1\%$ ,  $SD = 6.8$ ) had a significantly lower use of regenerative braking than the *speed recommendation* group ( $M = 78.2\%$ ,  $SD = 7.3$ ),  $t(30.27) = 3.45, p = .005, d = 1.15$  (large effect).

In the [MP5] *constant driving*, there were significant group differences concerning mean velocity and the difference to the optimal velocity (large effects). Games–Howell post-hoc tests revealed significant differences between the *control* group and the *speed recommendation* group concerning mean velocity and difference to the optimal velocity,  $t(43.91) = 2.83, p = .019, d = 0.83$  (large effect) and  $t(44.78) = 3.24, p = .006, d = 0.95$  (large effect). The *speed recommendation* group had a significantly lower mean velocity ( $M = 56.4, SD = 5.2$ ) as well as a lower difference to the optimal velocity ( $M = -1.5, SD = 2.5$ ) than the *control* group ( $M = 59.9, SD = 3.7$  and  $M = 1.0, SD = 2.8$ ).

## 6.6. Discussion

### Summary of Results

The objective of the present research was to examine how different ecodriving feedback approaches in BEVs affect drivers' knowledge (gaps, references, accuracy), uncertainty, ecodriving behaviour, and performance, thereby providing insights for optimising feedback systems according to actual cognitive needs.

Regarding **RQ1**, several misconceptions were observed across all feedback approaches regarding the verbalised driving strategies. These included incorrect assumptions about optimal acceleration intensity, misunderstandings of the relationship between pedal input and vehicle behaviour, and confusion between neutral gliding and regenerative braking. In addition, many

statements were vague, context-independent, or relied on avoidance-based phrasing. Core BEV-specific concepts, such as neutral gliding, conversion efficiency, or the aerodynamic implications of high speeds, were rarely mentioned and often misunderstood. Drivers receiving speed recommendations referred significantly more often to information from the vehicle and the environment to which attention must be paid (i.e., input information, information acquisition) compared to no feedback. Primarily, information on what to do with the vehicle controls (output information) was mentioned in the tips.

Regarding **RQ2**, the feedback approach had no meaningful influence on knowledge accuracy with small to medium effect sizes.

Regarding **RQ3**, the feedback approach had significant effects on the uncertainty due to a lack of knowledge across different MPs and regarding [MP1] *acceleration from standstill*, with participants receiving speed recommendations reporting lower uncertainty than those receiving no feedback. The effect sizes were medium to large.

Regarding **RQ4**, the feedback approach had no effects on the manoeuvre-specific mean consumptions and only selective behavioural effects in [MP5] *constant driving* and [MP3] *braking to lower speeds* with large effect sizes. Regarding [MP3] *braking to lower speeds*, the *consumption trace* group exhibited a significantly higher reliance on mechanical braking and lower use of regenerative braking than the other groups. The *speed recommendation* group drove significantly slower than the *control* group regarding the manoeuvre [MP5] *constant driving*. No significant group differences emerged for behavioural metrics in manoeuvres such as [MP4] *stopping*, [MP1] *acceleration from standstill*, or [MP2] *acceleration to higher speeds*, suggesting that feedback had limited influence on driving performance outcomes in these contexts.

## Implications

### *Uncertainty Due to a Lack of Knowledge versus Actual Knowledge*

Interestingly, the significantly reduced uncertainty in the *speed recommendation* group did not translate into a significantly higher knowledge accuracy. This suggests that although drivers felt more certain in their action regulation based on their knowledge, this confidence was not reflected in their ability to formulate accurate (i.e., correct and precise) tips. A possible explanation is that drivers in this group felt more supported by the implementation-related (i.e., output-function-related, relating this to a more abstract control-theoretic level) feedback, leading them to underestimate their knowledge gaps. However, instead of unquestioningly trusting, the higher availability of information related to the input function could suggest that drivers may have tried to rationalise or contextualise the recommendations by linking them to

observable information from the vehicle and the environment. In addition, this raises the question of whether this feedback approach enables refinement of mental representations and fosters adaptive behaviour in novel driving situations. In contrast, drivers in the *consumption trace* condition could have engaged in a more knowledge-based evaluation process, as they had to comprehend the relationship between their driving behaviour and energy consumption on their own. However, the *consumption trace* did not lead to significantly better knowledge accuracy despite this potential deeper engagement. This complements previous findings that energy consumption in BEVs is difficult to understand and that efficiency judgments based on such feedback can be systematically biased (Moll & Franke, 2021; Neumann & Krems, 2016). Overall, several misbeliefs and low knowledge accuracy align with previous research showing several false beliefs of HEV drivers (Franke et al., 2016). Furthermore, previous research indicates that while many drivers know about ecodriving, this knowledge does not always translate into corresponding behaviour (Pampel et al., 2015, 2017). Our findings extend this understanding by demonstrating that the challenge is not only in behavioural implementation but also in the persistence of inaccurate, vague, avoidance-oriented, or context-independent knowledge structures, even when feedback is present.

### *Driving Behaviour and Performance*

Only isolated behavioural differences were found across conditions, and no significant differences in energy consumption were observed. The absence of improvement in energy consumption contrasts with several previous studies reporting significant effects of real-time speed recommendations, emission curves, or consumption displays on performance (e.g., Allison et al., 2019; Chada et al., 2022; Stillwater & Kurani, 2014; Zhao et al., 2015), although consumption feedback has not always been associated with performance benefits in past research (Dahlinger et al., 2018). The behavioural driving performance differences suggest that consumption feedback may have inadvertently encouraged more reactive, less energy-efficient deceleration strategies. At first glance, the lower use of regenerative braking in the *consumption trace* group than in the *speed recommendation* group appears counterintuitive. A plausible explanation is that the speed recommendations prompted participants to initiate braking earlier, which allowed longer periods of regenerative deceleration. Although the recommended speed trajectory may have been difficult to follow precisely, starting to brake in advance may have increased the likelihood of energy being recovered by regenerative braking. In contrast, participants in the *consumption trace* group may have initiated braking too late or too abruptly, thereby engaging mechanical brakes more often and reducing opportunities for regenerative braking. Based on the assumption that consumption displays positively reinforce regenerative braking behaviour as they fail to show energy conversion losses (Franke, Görge, et al., 2019), one might have expected the *consumption trace* group to show higher use of regenerative

braking than the control group. However, this was not the case. Regarding constant driving, the *speed recommendation* group maintained lower mean speeds and stayed rather below the energy-optimal velocity. These differences suggest that implementation-oriented feedback can support speed regulation in alignment with energy efficiency goals, but may not equally foster efficient behaviour in more dynamic or complex manoeuvres, such as braking or accelerating.

### *Bridging the Knowledge Gap*

The present research suggests that increased confidence does not necessarily imply better understanding or improved ecodriving strategies. Neither recommendation systems nor consumption feedback alone sufficiently supports constructing precise, transferable knowledge structures for energy-efficient driving. The focus, however, was not on transforming drivers into technical experts with exhaustive system knowledge, but on empowering them to form adequately precise mental models that enable effective behavioural regulation, free of misconceptions and aligned with system-level processing. Otherwise, knowledge gaps may foster misconceptions, situationally fragile strategies, and misplaced confidence, ultimately limiting both learning and long-term efficiency gains. More broadly, the results suggest that current feedback designs may not fully realise their potential to promote active learning, as they led only to isolated behavioural adjustments without performance improvements. While drivers may feel supported, this confidence seems to reflect situational ease rather than robust cognitive clarity.

Feedback approaches should engage drivers in active decision-making and meaningful sensemaking to resolve this gap instead of only recommending behaviour. Interfaces that merely lower cognitive demand may help users act without supporting reasoning about cause-and-effect relations. Thus, mental representations may remain too imprecise and behaviour not sufficiently routinised, both for effective short-term activation, as shown in previous research (Pampel et al., 2015, 2017), and for long-term behavioural change already identified as challenging (Beusen et al., 2009; Wu et al., 2015). A promising direction lies in feedback that links driver inputs and system-level reasoning with driver actions in an interpretable and transparent manner. Such an approach may foster more stable, generalisable mental representations and reduce the reliance on context-specific cues. Besides, closing the gap between perceived and actual knowledge through targeted feedback and education could significantly enhance learning outcomes and overall ecodriving performance (Clayton & Clayton, 2024). Ensuring that individuals develop an accurate perception of their competence is essential for fostering informed and adaptive ecodriving behaviours.

The trade-off between user experience and actual cognitive representations with distinct patterns in verbalisable input information highlights a broader issue in subjective usability

assessments, which often evaluate criteria like confidence, ease of use, perceived effectiveness, and satisfaction but rarely differentiate between different levels of information processing (i.e., information acquisition, information analysis, decision selection, action implementation) and the role of mental representations within action regulation. However, a differentiated method seems necessary to better understand the effects of the feedback approaches.

Ultimately, improving ecodriving performance requires more than enhancing confidence. It demands knowledge-based approaches such as explainable ecodriving recommendations (i.e., explainable artificial intelligence; Miller, 2019) that may enable drivers to recognise, reflect on, and refine their understanding of energy-related dynamics. Clarifying the distinction between knowing what to do and understanding why it works is essential for fostering adaptive, context-sensitive driving strategies.

### **Limitations**

Several limitations should be considered when interpreting the findings of this study: methodological constraints in energy efficiency assessments, limitations in knowledge measurement, and statistical power.

#### *Energy Efficiency Assessments*

Interpreting energy efficiency at the manoeuvre level is methodologically complex. Automatic detection isolates acceleration, braking, and constant driving but does not account for the context before or after a manoeuvre. For example, a short, intense acceleration may precede a longer high-speed phase, while a shorter high-speed phase follows a long, weak acceleration. Without controlling for necessity (e.g., accelerating to compensate for an unnecessary previous slowdown) or ensuring consistent spatial segments, comparisons become problematic, especially given interindividual variation in manoeuvre frequency, duration, and location. Analysing fixed-length segments, as a potential solution, would fail to account for participants who exhibit more frequent vs. fewer accelerations and selectively sample behaviour in a way that may not be representative.

#### *Knowledge Measurement and Cognitive Availability*

Only the verbalised parts of participants' knowledge could be assessed, as no method fully captures mental representations. Even if implicit differences existed, they did not translate into measurable performance benefits. Participants may also have been less motivated, particularly in self-report tasks, as the online questionnaire followed a demanding driving simulator study. The limited references to comparator and input functions may reflect low engagement or

limited competence. Verbalisations likely reflected what was most cognitively available, influenced by recent use, motivation or competence. Future research should explore mental representations across contexts and include perceived support of drivers' mental representations as a complementary usability construct.

#### *Statistical Power*

The relatively small and unequal group sizes ( $n = 15, 23, 25$ ) limited statistical power (estimated at 0.39 for moderate effects,  $f = 0.25$ ,  $\alpha = .05$ ), increasing the risk of Type II errors. Achieving 80% power would have required at least 50 participants per group. When combined with variance heterogeneity, unequal sample sizes can inflate Type I error rates. This was partially addressed using Welch's ANOVAs, which adjust for unequal variances. Small samples can also lead to unstable effect size estimates. For example, there were small to moderate effects ( $\eta^2 = 0.03-0.13$ ) regarding uncertainty, but pairwise comparisons (e.g., speed recommendation vs. consumption trace) may have been underpowered. Similar limitations apply to other dependent variables.

## **6.7. Conclusion**

The findings suggest that feedback approaches influence drivers' subjective certainty differently but do not necessarily improve objective driving performance. In our study, several false beliefs and low knowledge accuracy were observed across all feedback conditions. While recommendations can reduce uncertainty, they may also foster overconfidence. Typical consumption feedback may also fall short of providing actionable guidance for behaviour change and adequate formation of mental representations. Ultimately, the efficacy of ecodriving feedback approaches in supporting energy-efficient driving likely depends on the alignment between drivers' perceived competence, actual knowledge, and the feedback's cognitive demands.

Designing interfaces that align perceived support with actual learning and performance improvements remains a key challenge. This includes identifying feedback designs that enhance subjective certainty and enable drivers to refine misbeliefs, adapt strategies across contexts, and calibrate their confidence in line with objective performance.

Future research should investigate how personalised and explainable feedback mechanisms, transparently linking driver actions to energy dynamics, can foster active sensemaking and the development of adequate mental representations, thereby closing the gap between perceived and actual competence to enable sustained behavioural adaptation.

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## 6.10. Appendix

### Appendix A: Generation Process of Ideal Reference Responses

Formulating tips for energy-efficient driving, such as maintaining constant speed, presents a key methodological challenge due to the gap between complex vehicle dynamics and how drivers cognitively represent and communicate their mental representations in a simplified way. Physical systems involve complex nonlinear interactions, like kinetic and potential energy, aerodynamic drag, or battery electrochemistry, that resist simple if-then verbalisation. Conversely, mental representations tend to use simplified causal rules, which are essential for decision-making in dynamic, hierarchical control systems like driving, where multiple control loops operate at different levels (e.g., manoeuvre versus route level).

For instance, optimal energy efficiency on a single manoeuvre may prioritise local speed and immediate conditions, while route-level strategies consider overall range and travel time. Drivers with elaborated mental representations understand how combining different manoeuvre strategies across route sections (e.g., lower average speeds on highways but utilising speed limits elsewhere) balances efficiency and journey time. This analysis focuses on individual manoeuvre-level representations, acknowledging the persisting challenge of simplification.

Constant speed is particularly complex because it depends on various minor environmental factors, not just one dominant variable. While physically, constant speed reduces energy-intensive acceleration phases, a simple instruction like “keep your speed constant” neglects factors such as topography, traffic, and vehicle specifics. The challenge lies in abstracting this complexity into actionable yet precise rules. This calls for adaptive, dynamic guidelines rather than fixed prescriptions, such as “adjust mean speed anticipatorily based on topography and traffic to minimise energy use” (i.e., driving to keep inertia; Lucas-Alba et al., 2020). This dynamic principle is exemplified by MPC in speed recommendations, which optimises strategies in real time. Similarly, human decision-making could benefit from a dynamic approach by providing simplified rules that promote an understanding of underlying mechanisms.

The central methodological question is: How can complex physical relationships be simplified into communicable rules that guide action without oversimplifying and causing misinterpretations? Addressing this is crucial for designing effective driving strategies and highlights that mental representations are both necessary and integral to controlling complex systems. To operationalise this, drivers’ verbalised tips and technical explanations were compared to systematically derived ideal reference responses rather than raw physics-based

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models. These references were developed by deriving prototype tips from driving data and refining them with a panel of four (engineering) psychology experts with a mean experience of 8.6 years. They reviewed textual problem descriptions (e.g., “choose the lowest possible speed,” “drive at constant speed,” “glide neutrally alternating with optimal accelerations”) and consolidated their simplifications into ideal references.

**Appendix B: Group Differences in Sample Characteristics****Table B1***Analysis of Group Differences in Sample Composition*

Variable	Test	Statistic	<i>p</i>	$\epsilon^2$	<i>V</i>
Total driving experience across all vehicles (km)	Kruskal–Wallis	<i>H</i> (2)	1.09	.579	.02
Total driving experience with BEV (km)	Kruskal–Wallis	<i>H</i> (2)	4.25	.120	.27
Age	Kruskal–Wallis	<i>H</i> (2)	2.66	.264	.04
Ecodriving motivation	Kruskal–Wallis	<i>H</i> (2)	4.14	.126	.07
Ecodriving knowledge	Kruskal–Wallis	<i>H</i> (2)	2.47	.291	.04
Technical background knowledge	Kruskal–Wallis	<i>H</i> (2)	4.55	.103	.07
Affinity for technology interaction (ATI)	Kruskal–Wallis	<i>H</i> (2)	5.78	.055	.09
Gender	Chi-square	$\chi^2$ (2)	1.24	.537	.14
Education Level	Chi-square	$\chi^2$ (6)	8.86	.182	.27

*Note.*  $n_{control} = 25$ ,  $n_{consumption} = 15$ ,  $n_{recommendation} = 23$ .

## Appendix C: Qualitative Analyses

Table C1

*Qualitative Analysis of False and Missing Beliefs (N = 63)*

Cluster	Stopping		Braking to lower speeds		Accelerating from standstill		Accelerating to higher speeds		Constant driving	
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
No reference to neutral gliding	63	100.0	63	100.0	-	-	-	-	62	98.4
No explicit reference to acceleration intensity <sup>a</sup>	-	-	-	-	19 <sup>b</sup>	30.2	20	31.7	-	-
No reference to motor efficiency (map)	-	-	-	-	61	96.8	62	98.4	61	96.8
No reference to air resistance	-	-	-	-	-	-	-	-	63	100.0
Pedal release = "roll out" (i.e., coasting)	17	27.0	13	20.6						
Maximise recuperation	7	11.1	9	14.3						
Recuperation misunderstood as coasting	7 <sup>c</sup>	11.1 <sup>c</sup>	5 <sup>c</sup>	7.9 <sup>c</sup>						
Braking pedal consumes energy	3	4.8	5	7.9					1	1.6
Start braking process late	1	1.6	2	3.2						
Alternate between driving and braking pedals			1	1.6						
Hard braking minimises energy loss	1	1.6								
Recuperation is more efficient than coasting	1	1.6								
Accelerate slow					30	47.6	34	54.0		
Accelerate fast					5	7.9	5	7.9		
Pedal pressure variation over time					3	4.8	3	4.8		
Accelerate stepwise					1	1.6	1	1.6		
Accelerate like from standstill							1	1.6		
Constant pedal position									13	20.6
Cruise control = most efficient									20	31.8
Constant pedal = constant speed									3	4.8
Constant speed is more efficient than PnG									1	1.6
Exhausting the maximum speed									1	1.6

*Note.* Manoeuvre-irrelevant beliefs are marked with hyphens. PnG = pulse and glide.

<sup>a</sup> Either only an abstract formulation of avoiding behaviour (i.e., avoid full-throttle) or no reference at all

<sup>b</sup> Including six persons for whom an implicit interpretation of slow acceleration would theoretically be possible.

<sup>c</sup> Persons are not included in "Maximise recuperation" as they only referred to "coasting" in tips.

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**Table C2**

*Qualitative Analysis of Pedal Interactions, External Information, Anticipating, and Formulation Patterns (N = 63)*

Cluster	Stopping		Braking to lower speeds		Accelerating from standstill		Accelerating to higher speeds		Constant driving	
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
<i>Pedal interactions</i>										
No pedal interaction specified at all	14	22.2	16	25.4	32	49.2	40	63.5	20	31.8
Driving pedal interaction explicitly	40	63.5	37	58.7	31	49.2	23	36.5	36	57.1
Driving pedal interaction implicitly									7	11.1
Braking pedal interaction explicitly	15	23.8	8	12.7	3	4.8	1	1.6	6	9.5
Braking pedal interaction implicitly	19	30.2	24	38.1					10	15.9
<i>External information and anticipating</i>										
Traffic signs and signals	26	41.3	11	17.5	4	6.3	7	11.1	4	6.4
Vehicle information (e.g., speedometer, consumption, sound)	13	20.6	11	17.5	10	15.9	7	11.1	10	15.9
Vehicle information (RPM)					3	4.8	1	1.6		
Target/desired speed					7	11.1	9	14.3	3	4.8
Avoid speed fluctuations	8	12.7	3	4.8					46 <sup>a</sup>	73.0 <sup>a</sup>
Considering traffic	1	1.6	2	3.2	1	1.6				
Slope and/or road course	5	7.9	3	4.8	4	6.3	3	4.8	11	
<i>Formulations</i>										
Avoidance framing in behavioural formulations (i.e., avoid full-throttle or abrupt accelerations)	27	42.9	18	28.6	26	41.3	20	31.7	20	31.8
Generic behavioural formulations	19	30.2	25	39.7	33	52.4	38	60.3	29	46.0
Generic energy-related reasoning (e.g., "lower consumption")	27	42.9	18	28.6	40	63.5	39	61.9	23	36.5
Generic recuperation-related reasoning	18	28.6	18	28.6						
Explicit references to combustion vehicles (e.g., gear, RPM, braking distance)	2	3.2	2	3.2	5	7.9	5	7.9	1	1.6
No explicit energy-related reasoning (e.g., preservation/wear, avoid speed fluctuation, no explanation at all)	17	27.0	15	23.8	20	31.7	25	39.7	28	44.4

*Note.* <sup>a</sup> All participants referring explicitly/implicitly to constant speed or avoiding speed fluctuations.

**Appendix D: Feedback Effects and Driving Metrics****Table D1***Effects of the Feedback Approach on Knowledge Accuracy and Uncertainty Due to a Lack of Knowledge*

Variable	Method	Test statistic	$p$	$\eta^2$	$\epsilon^2$
<i>Knowledge accuracy</i>					
Across all manoeuvres	ANOVA	$F(2, 60)$	2.17	.124	.12
Stopping	Kruskal–Wallis	$H(2)$	2.92	.232	.05
Braking to lower speeds	Kruskal–Wallis	$H(2)$	3.39	.183	.06
Accelerating from standstill	Kruskal–Wallis	$H(2)$	1.24	.537	.02
Accelerating to higher speeds	Kruskal–Wallis	$H(2)$	5.77	.056	.09
Constant driving	Kruskal–Wallis	$H(2)$	0.58	.750	.01
<i>Uncertainty due to a lack of knowledge</i>					
Across all manoeuvres	Welch ANOVA	$F(2, 32.52)$	4.32	.022	.11
Stopping	Welch ANOVA	$F(2, 33.68)$	2.10	.138	.06
Braking to lower speeds	Welch ANOVA	$F(2, 35.42)$	0.76	.475	.03
Accelerating from standstill	Welch ANOVA	$F(2, 34.31)$	4.66	.016	.13
Accelerating to higher speeds	Welch ANOVA	$F(2, 33.54)$	3.03	.062	.08
Constant driving	Welch ANOVA	$F(2, 33.62)$	3.15	.056	.09

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**Table D2**

*Descriptive Statistics of Non-Standardised Driving Performance Metrics*

Metric	Pre trial			Experimental trial		
	Control	Cons	Rec	Control	Cons	Rec
	<i>M (SD)</i>	<i>M (SD)</i>	<i>M (SD)</i>	<i>M (SD)</i>	<i>M (SD)</i>	<i>M (SD)</i>
<i>Acceleration from standstill</i>						
Mean consumption (Wh)	0.50 (0.14)	0.51 (0.22)	0.56 (0.17)	0.54 (0.15)	0.53 (0.18)	0.51 (0.18)
Median of throttle position	0.44 (0.10)	0.46 (0.17)	0.47 (0.14)	0.46 (0.12)	0.45 (0.17)	0.41 (0.12)
Median of acceleration (m/s <sup>2</sup> )	1.43 (0.33)	1.50 (0.54)	1.56 (0.44)	1.47 (0.40)	1.46 (0.54)	1.41 (0.40)
<i>Acceleration to higher speeds</i>						
Mean consumption (Wh)	0.65 (0.09)	0.65 (0.10)	0.64 (0.11)	0.63 (0.09)	0.62 (0.11)	0.61 (0.10)
Median of throttle position	0.27 (0.03)	0.27 (0.02)	0.27 (0.03)	0.26 (0.03)	0.26 (0.03)	0.26 (0.04)
Median of acceleration (m/s <sup>2</sup> )	0.63 (0.09)	0.65 (0.10)	0.66 (0.11)	0.60 (0.09)	0.59 (0.10)	0.63 (0.11)
<i>Braking to lower speeds</i>						
Mean consumption (Wh)	-0.60 (0.06)	-0.59 (0.04)	-0.58 (0.07)	-0.59 (0.06)	-0.60 (0.05)	-0.58 (0.05)
Neutral gliding (proportion)	15.24 (9.27)	14.29 (9.86)	13.50 (8.66)	14.40 (8.92)	14.21 (6.26)	12.75 (6.00)
Regenerative braking (proportion)	70.59 (11.91)	72.63 (10.77)	74.79 (9.18)	74.18 (10.66)	70.13 (6.83)	78.15 (7.30)
Mechanical (proportion)	14.17 (7.21)	13.09 (3.71)	11.70 (4.39)	11.41 (4.74)	15.66 (4.20)	9.10 (4.32)
Median of acceleration (m/s <sup>2</sup> )	-1.02 (0.17)	-1.07 (0.13)	-1.03 (0.13)	-1.02 (0.12)	-1.04 (0.12)	-0.97 (0.09)
<i>Stopping</i>						
Mean consumption (Wh)	-0.21 (0.11)	-0.18 (0.15)	-0.19 (0.12)	-0.28 (0.11)	-0.25 (0.17)	-0.24 (0.13)
Neutral gliding (proportion)	9.04 (9.34)	8.14 (5.83)	10.52 (7.72)	7.19 (5.92)	7.70 (8.77)	9.26 (7.82)
Regenerative braking (proportion)	34.85 (18.07)	32.80 (25.25)	32.21 (15.17)	45.95 (17.43)	43.20 (26.21)	36.09 (16.70)
Mechanical (proportion)	56.12 (0.68)	59.06 (27.22)	57.27 (16.71)	46.86 (18.32)	49.10 (26.45)	54.66 (17.71)
Median of acceleration (m/s <sup>2</sup> )	-1.51 (0.68)	-1.26 (0.29)	-1.31 (0.31)	-1.49 (0.29)	-1.47 (0.26)	-1.40 (0.47)
<i>Constant driving</i>						
Mean consumption (Wh)	0.08 (0.03)	0.08 (0.07)	0.09 (0.07)	0.07 (0.05)	0.09 (0.07)	0.11 (0.06)
Mean velocity (km/h)	58.16 (4.00)	56.10 (6.25)	57.83 (5.80)	59.92 (3.68)	57.59 (3.90)	56.36 (5.16)
Mean velocity-optimum difference (km/h)	0.91 (4.35)	-1.10 (3.24)	-1.52 (3.27)	1.00 (2.82)	-0.52 (1.85)	-1.47 (2.53)

*Note.* Cons = consumption trace, Rec = speed recommendation.

## 7. Study 3: Better Mental Model, Fewer Watt-Hours? Effects of Ecodriving Tips on Knowledge, Action Regulation, and Driving Performance in Battery Electric Vehicles

### 7.1. Abstract

Supporting users in avoiding waste of valuable resources like energy is a key objective in optimising system design. Particularly in battery electric vehicle (BEV) operation, energy efficiency depends on driver behaviour, i.e., on adequate understanding of energy dynamics. Building on the theoretical relevance of know-how and know-why knowledge (e.g., in the form of mental models) for successful action regulation, this study examines how ecodriving tips can be communicated efficiently and what depth of information is required. Specifically, we investigate whether compact, generic tips suffice, or whether psychologically structured information—linking action instructions with system rationale—more effectively support ecodriving. In a field experiment, participants ( $N = 50$ ) drove an 11 km urban route comprising multiple energy-relevant driving situations in a Nissan LEAF BEV. Participants were randomly assigned to receive either (G1) no tips, (G2) compact generic tips, or (G3) psychologically comprehensive tips integrating action guidance with explanatory rationale (know-how-and-why). Contrast analyses revealed a consistent linear trend across groups, indicating gradual improvements from G1 to G3. Participants in G3 demonstrated the lowest energy consumption (–11.3% vs. G1), more moderate and stable throttle use, and the most consistent velocity. They reported the highest perceived support for action regulation and the mental model, along with the largest gain in perceived ecodriving knowledge. These findings highlight the importance of aligning information structure with cognitive needs. Implications concern cognitively aligned in-vehicle support systems and scalable interventions for driver education and sustainable transport.

**Keywords:** Ecodriving, energy efficiency, battery electric vehicles, action regulation, information processing, mental model

### 7.2. Introduction

Supporting energy-efficient driving is crucial for sustainable mobility. In battery-electric vehicles (BEVs), ecodriving provides economic advantages, can fulfil psychological needs (e.g., environmental awareness), and enhances coping with low-battery situations (Barkenbus, 2010; Bingham et al., 2012; Franke et al., 2015; Rolim et al., 2012). While technological advancements in BEVs improve efficiency, actual energy savings always largely depend on driver behaviour, making ecodriving key to avoid waste of valuable resources (Braun & Rid, 2018; Kubik et al., 2023; Kumar, 2024; Opetnik et al., 2024).

Driving is a cognitively demanding task involving vehicle control, speed adjustment, and strategic decision-making (Young et al., 2011), with over 1,600 individual tasks identified (Walker et al., 2001). Ecodriving increases this complexity further (Barkenbus, 2010; Tulusan et al., 2012), particularly in electric vehicles (EVs), where unique and less intuitive energy dynamics like regenerative braking, higher imperceptibility, and volatility of energy flows affect efficiency (Franke et al., 2016; Neumann et al., 2015). Particularly compared to internal

combustion engine vehicles (ICEVs), operational-level ecodriving (Sivak & Schoettle, 2012) plays a central role in determining energy efficiency and directly impacts energy consumption (Bingham et al., 2012; Birrell et al., 2014; Franke et al., 2017; Huang et al., 2018, 2021; Ma et al., 2024; Wang et al., 2020; Yan et al., 2021).

Interventions to improve ecodriving have been widely studied, particularly in ICEVs, where energy efficiency is directly linked to fuel consumption and emissions (Allison et al., 2021; Beloufa et al., 2019). Onboard ecodriving feedback has improved fuel efficiency, with an average reduction of 6.6% across multiple studies, though effects vary widely depending on feedback design and implementation (Sanguinetti et al., 2020). While these approaches highlight the potential of human-centred driver-vehicle interaction to promote sustainable BEV usage, they also raise questions about the transferability of traditional ecodriving strategies to BEVs, given their distinct energy dynamics (Allison et al., 2021).

Effective ecodriving interventions for BEVs require a precise understanding of how drivers process energy-relevant information, learn and effectively implement ecodriving through the lens of control-theoretic models of behaviour. Following control-theoretical perspectives (Carver & Scheier, 1982; Macadam, 2003; Powers, 1973; Powers et al., 2011), ecodriving can be understood as a self-regulation process (i.e., a negative feedback loop comparable to similar models of safety-related driver control behaviour; Fuller, 2011; Lewis-Evans et al., 2013). In this process, drivers perceive energy-efficiency-related vehicle and environmental information (input function), compare this current state to a reference or goal state (reference function), adjust their behaviour accordingly (output function), and refine their strategies by going through multiple feedback loops in the long term (Franke et al., 2016). Additionally building on human information processing (e.g., Parasuraman et al., 2000; Wickens & Carswell, 2021), behavioural control can be conceptualised as involving four stages: (1) information acquisition (perceiving relevant energy-related information), (2) information analysis (deriving strategies' subjective utility and reference value, evaluating current versus target states), (3) decision (selecting an appropriate strategy), and (4) implementation of behaviour. Thus, the effectiveness of this information processing within the behavioural control loop depends on how well drivers interpret efficiency-related information and recognise the causal relationships between their actions and energy consumption. However, efficiency feedback is often difficult to comprehend and may lead to misjudgements (Gödker et al., 2024; Moll & Franke, 2021).

A key factor in overcoming these challenges is the development of adequate mental representations (i.e., *mental models*, *scripts*, or *schemas*; Baumann & Krems, 2007; Endsley, 2000). These representations can help drivers to integrate prior knowledge and contextual information, anticipating energy efficiency outcomes and adapting their strategies even in unfamiliar situations (Baumann & Krems, 2009; Carroll & Olson, 1988). Since energy-efficient

driving strategies vary by context, drivers can be expected to rely on prior knowledge and expectations to determine the most effective approach (Franke et al., 2016). However, given that BEV energy dynamics are difficult to perceive, particularly without prior experience (Neumann et al., 2015), even experienced drivers show inefficient driving patterns (Huang et al., 2021). This may reflect limitations in the current form and depth of ecodriving knowledge, as even existing knowledge is frequently not translated into actual driving behaviour (Pampel et al., 2015, 2017).

Accordingly, there is a need for structured interventions that support knowledge acquisition and foster the development of mental representations, thereby facilitating adaptive, energy-efficient behaviour in real-world driving. Text-based interventions are a promising, cost-effective, and scalable approach (Günther et al., 2019), as they can systematically present procedural and conceptual information, potentially supporting learning and expanding one's knowledge (Van Den Broek, 2010). While simple fundamental textual interventions (e.g., tips or advice) or explaining ecodriving rules have been shown to reduce fuel consumption and enhance ecodriving behaviour (Andrieu & Saint Pierre, 2012; Azzi et al., 2011; Beloufa et al., 2019; Günther et al., 2019; van der Voort et al., 2001), existing guidelines often remain too generic and context-free (e.g., Dacia, 2024; Tesla, 2024b; see also Sureth et al., 2019). Furthermore, previous studies have investigated ecodriving tip-based feedback primarily in ICEVs using driving simulators (Beloufa et al., 2019; van der Voort et al., 2001) or field studies (Andrieu & Saint Pierre, 2012; Günther et al., 2019; Sureth et al., 2019), with a strong focus on visual or text-based feedback. Beyond the focus on vehicle type, another major limitation in previous research is the lack of systematically derived ecodriving feedback. Moreover, existing research with BEVs has predominantly examined experienced drivers (Sureth et al., 2019), leaving the effectiveness of ecodriving interventions for those with little to no BEV experience underexplored. Some field studies were examined on a predefined route but did not systematically compare interventions to alternative formats and/or did not detail the training intervention content (Andrieu & Saint Pierre, 2012; Günther et al., 2019), leaving it unclear how different text-based ecodriving strategies influence behaviour. Additionally, prior research has rarely investigated how drivers experience uncertainty in specific driving situations where they struggle to apply energy-saving strategies, an aspect that Sureth et al. (2019) identified as a critical limitation in previous studies.

Addressing these gaps requires interventions that are both structured and tailored to drivers' cognitive control processes. Many interventions were based on generic fuel-saving guidelines (e.g., Andrieu & Saint Pierre, 2012; van der Voort et al., 2001) rather than systematically structured ecodriving principles validated by experts (e.g., Sureth et al., 2019). Consequently, textual information was not explicitly tailored to support cognitive processing within the

behavioural control loop, limiting its effectiveness in behavioural adaptation. Research suggests that integrating how to implement ecodriving strategies (*know-how*) and explanations of why this behaviour is energy-efficient (*know-why*; Arend et al., 2019) can enhance ecodriving performance, yet empirical studies of these approaches in ecodriving contexts remain scarce. One effective textual approach seems to be presenting if-then action plans (e.g., “If approaching a red light, then release the accelerator early to maximize coasting”; Gollwitzer, 1993, 1999). Such formulations enhance goal-directed behaviour by focusing attention on relevant situational cues and improving recall of the intended action (Achtziger et al., 2012; Sheeran et al., 2005). Their effectiveness has been demonstrated in driving-related studies, including reducing speeding behaviour (Brewster et al., 2015, 2016; Elliott & Armitage, 2006) and lowering mobile phone use while driving (Elliott et al., 2021). In another textual approach, Sureth et al. (2019) investigated different formulations of ecodriving tips for hybrid electric vehicles (HEVs). They found that only combining *know-how* with *know-why* led to significant improvements in energy efficiency.

Building on the question of how ecodriving knowledge should be communicated and what level of depth is required, it is also critical to consider how interventions support drivers across the distinct information processing stages involved in action regulation. Yet, intervention effectiveness in BEVs has predominantly been assessed through performance measures and global subjective self-reports, without differentiating effects across specific regulatory phases. Although subjective self-reports could provide, in principle, a more differentiated assessment of intervention impacts (e.g., knowledge, usability, acceptance, or satisfaction; Allison et al., 2019; Günther et al., 2019; Lai, 2015; S.-S. Lee et al., 2011; Staubach et al., 2014), prior studies have not investigated how interventions influence information acquisition, information analysis, decision selection, or behavioural implementation separately.

These findings underscore the importance of cognitively aligning information structure with user needs by promoting both action implementation and system understanding. However, it remains an open question how textual interventions shape mental models and support behavioural adaptation towards energy-efficient driving in BEVs. The present study addresses this issue by examining the impact of psychologically structured, scalable textual interventions that combine *know-how* and *know-why* elements, aiming to enhance drivers' comprehension of system dynamics, improve ecodriving behaviour, and increase perceived support for energy-efficient action regulation during BEV operation.

These considerations highlight the importance of designing structured, cognitively aligned interventions that promote action regulation and system understanding. However, it remains an open question how scalable, textual interventions should be communicated and what level of

information depth is required to effectively support mental representations and behavioural adaptation towards energy-efficient driving in BEVs remains an open question.

### 7.3. Present Research

To advance the understanding of how structured textual interventions influence ecodriving behaviour and perceived support in action regulation, the present study systematically compared three informational formats: (1) no information (*control*), (2) compact generic ecodriving tips (*generic*), and (3) psychologically comprehensive tips integrating action guidance with explanatory rationale (*know-how-and-why*). Building on the conceptual rationale above, the study employed a field experiment on a predefined route, comprising multiple energy-relevant situations.

A central assumption of this study is that the know-how-and-why tips should support action regulation (i.e., from the usability and information processing perspective) as well as the *mental model* (i.e., perceiving the provided information as useful for structuring the understanding of BEV ecodriving) more effectively than compact generic tips. This advantage should be reflected in improved performance, greater gains in feeling knowledgeable (e.g., "I can explain to other people how they can drive energy-efficiently with an electric vehicle"), and reduced perceived uncertainty due to a lack of knowledge. These assumptions are based on the idea that psychologically comprehensive tips clarify the causal mechanisms that link behavioural strategies to their energetic consequences (e.g., "If you accelerate from a standstill, then press the driving pedal moderately to optimise the energy-to-speed ratio and ensure optimal motor efficiency. This allows you to..."), while compact generic ecodriving advice is often abstract and context-independent (e.g., "Accelerate moderately"). By making relationships between behavioural strategy and its effect explicit (i.e., rule-based knowledge as a prerequisite for predicting outcomes, behavioural flexibility, and transfer; Osman, 2010), this can reduce uncertainty in selecting and applying appropriate driving behaviours. This may be especially relevant in unfamiliar or cognitively demanding driving contexts, such as driving a BEV for the first time.

More specifically, if-then formulations can direct attention to relevant situational cues and enhance the accessibility of appropriate strategies (Achtziger et al., 2012; Sheeran et al., 2005), thereby supporting the perceived support of the information acquisition stage. In the information analysis stage, explanatory tips may offer clearer reference points for assessing energy efficiency, such as comparing current versus target acceleration intensity. In decision selection, explicit links between situational conditions and recommended actions (if-then rules) could enable more accurate and faster strategy selection without relying on trial-and-error. In

the action implementation stage, precise explanations close to the action may support more accurate and confident behavioural implementation than more abstract formulations. Moreover, know-how-and-why tips could facilitate accurate and confident but also efficient action regulation, as well-structured information lowers mental effort by reducing the need for self-inference or problem solving during action execution (cognitive load theory; Sweller, 2003). Additionally, if-then formulations (i.e., *implementation intentions*; Achtziger et al., 2012; Gollwitzer, 1999) have been shown to improve automatic retrieval and reduce decision complexity, thus supporting more efficient behavioural regulation.

More specifically, the research questions and hypotheses are:

**RQ1** How do explanatory know-how-and-why tips affect ecodriving performance compared to generic tips and no information?

**H1** Participants in the *know-how-and-why* condition will demonstrate the best ecodriving performance, followed by those in the *generic* condition, with participants in the *control* condition showing the lowest performance.

**RQ2** How do explanatory know-how-and-why tips affect action regulation quality compared to generic tips and no information?

**H2** Participants in the *know-how-and-why* condition will perceive the greatest support of effective, efficient, and confident action regulation, followed by those in the *generic* condition, with participants in the *control* condition perceiving the lowest support.

**H3** Participants in the *know-how-and-why* condition will perceive the greatest support within all information processing stages, followed by those in the *generic* condition, with participants in the *control* condition perceiving the lowest support.

**H4** Participants in the *know-how-and-why* condition will perceive the greatest support of their *mental model* within action regulation, followed by those in the *generic* condition, with participants in the *control* condition perceiving the lowest support.

**H5** Participants in the *know-how-and-why* condition will report the lowest perceived uncertainty due to a lack of knowledge when applying ecodriving strategies in specific driving situations, followed by those in the *generic* condition, with participants in the *control* condition reporting the highest uncertainty.

**RQ3** What effects do explanatory know-how-and-why tips have on the development of perceived ecodriving knowledge compared to generic tips and no information?

**H6** Participants in the *know-how-and-why* condition will show the highest gain in perceived ecodriving knowledge, followed by those in the *generic* condition, with participants in the *control* condition showing the lowest gain.

## 7.4. Method

### Participants

Participants were recruited via the university mailing list, the university's learning management system forums, and a database of participants from previous studies. Participants had to be at least 18 years old, possess a driving license, and be fluent in German to be included in the experiment. All participants were compensated €15 for their time in the study or course credit for psychology and media informatics students. Ethics approval for this study was granted by the Ethics Committee of the University of Lübeck before the start of the experiment (file number 2024-439).

The resulting sample included 50 participants ( $N_{total} = 50$ ) between 19 and 68 years old ( $M = 32.0$ ,  $SD = 16.5$ ). Among them, 18 participants (36%) were female, and one did not indicate their gender. Additionally, 17 participants (34%) had a university degree. The total driving experience across all vehicles was  $M = 134364.3$  km ( $SD = 303325.3$ ). In total, 20 participants (40% of the sample) had driven at least 50 km in a BEV. Their total driving experience with BEVs was  $M = 7252.5$  km ( $SD = 26601.1$  km). A further 12 participants (24%) reported experience with (plug-in) HEVs. Regarding the Affinity for Technology Interaction (ATI; Franke et al., 2019), the sample showed a very wide range (ranging from 1.9 to 6.0), with a mean score of 4.1 above the scale midpoint. The mean and the standard deviation ( $SD = 1.2$ ) are higher than the average values reported for the general population ( $M = 3.6$ ,  $SD = 0.9$  to  $1.1$ ; Franke et al., 2019). Participants' self-reported motivation to drive energy-efficiently was above the scale midpoint ( $M = 4.1$ ,  $SD = 1.0$ , range = 2 to 6). Ecodriving motivation was measured with an 8-item scale based on Arend and Franke (2017), Franke et al. (2016), and previous research of the research group.

Of the final sample, three participants had largely corrupted driving data sets due to temporary technical problems in the data logging. Therefore, we excluded these datasets from all analyses that used driving simulator data (energy consumption and behavioural metrics), resulting in a reduced sample  $N' = 47$ .

## Procedure

Approximately one week before the scheduled driving task, participants completed the first part of the survey via LimeSurvey (LimeSurvey GmbH, 2012). The questionnaire included the creation of a personal alphanumeric code for pseudonymised data allocation and scales assessing driving experience, ecodriving knowledge, technical system knowledge, and ecodriving motivation. Participants were randomly assigned to the groups ( $n_{control} = 16$ ,  $n_{generic} = 16$ ,  $n_{know-how-and-why} = 18$ ). Tip groups' participants received a PDF document with a list of the respective ecodriving tips. They were instructed to read the tips carefully, to use them during the drive if needed, and not to share them with others. One day before the planned appointment, participants received a questionnaire reminder and were asked to revisit the tip list.

Before the participant arrived on the study day, the test supervisor connected the data logger, dashcam, and smartphone for navigation (see Figure 2). In addition, it was ensured that the battery was not charged above 80% using the vehicle's charging timer, as full recuperation was only available below this threshold. Upon arrival, participants received a standardised 15-minute briefing covering the procedure, the route, and the vehicle. The gears and settings of the Nissan Leaf were explained, although participants were not permitted to change any settings to ensure consistency in energy consumption. Specifically, they were instructed not to use the air conditioning, heating, steering wheel or seat heating, radio, or open the windows. The eco and one-pedal modes were also disabled, as these features support regenerative braking and would have automatically increased energy efficiency. The windscreen wipers were set to auto mode. The driver's license was checked, and the consent and data protection forms were signed.

Then, the participants followed the predefined route guided by the navigation system (see Figure 1). The route covered 11.0 kilometres and took an average of 21.8 minutes. It was selected specifically for this study because it required participants to perform many manoeuvres addressed in the ecodriving tips, such as braking at high speeds.

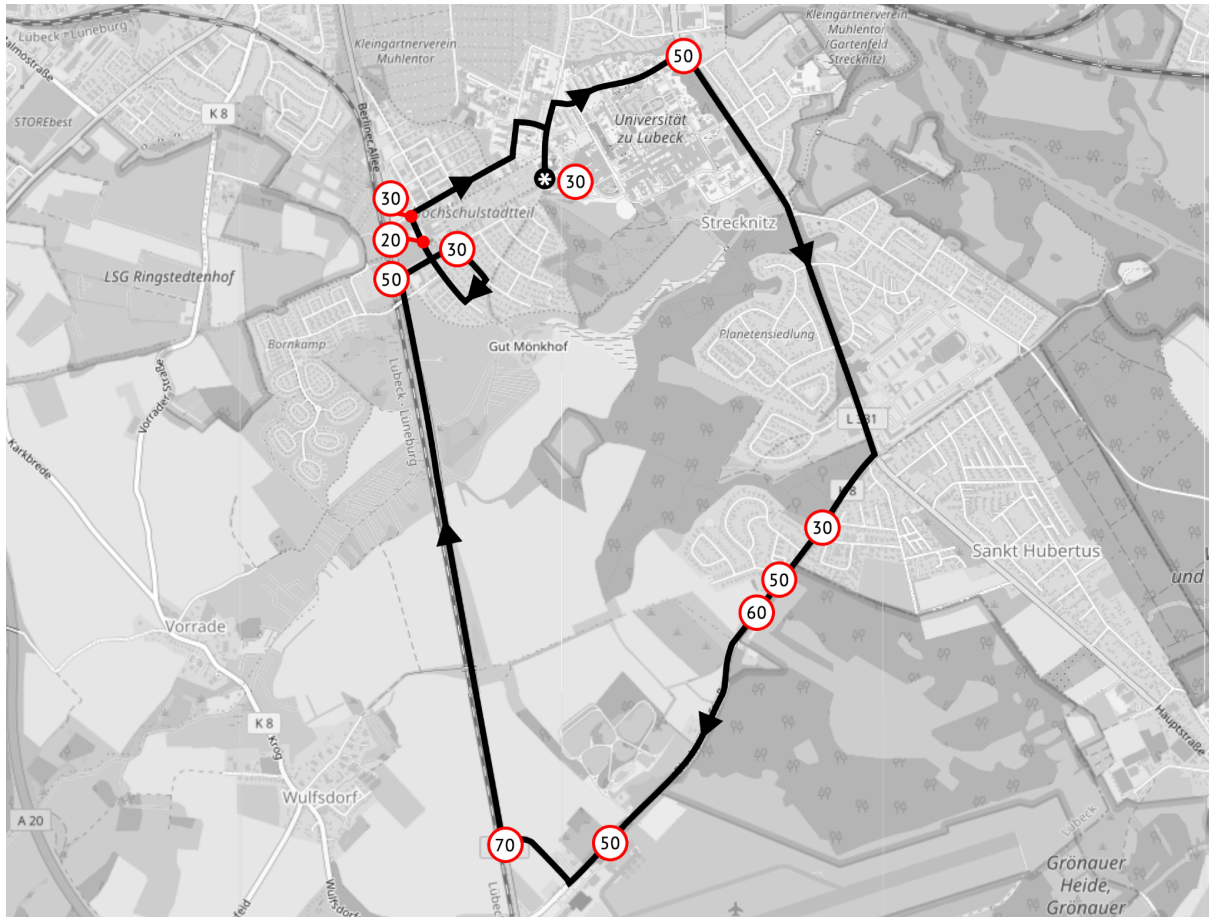
The route included a variety of traffic situations, including urban areas with speed limits of 50 km/h, low-speed zones with limits of 20 or 30 km/h, and rural segments with speed limits of 60 or 70 km/h, thus covering a wide range of ecodriving-relevant conditions.

After completing the drive, participants filled out the second online questionnaire. This included a re-entry of their pseudonymised code, subjective measures of action regulation, ecodriving knowledge, uncertainty due to a lack of knowledge, and sociodemographic information. Participants were also given the opportunity to provide open feedback in a

free-text field. In addition, those assigned to the tip groups answered further evaluation items not considered in the present research. The total duration of participation, including questionnaires, briefing, and the driving task, was approximately 1.3 hours per participant.

**Figure 1**

*Route with Speed Limits*



*Note.* Based on maps in the OpenStreetBrowser (OpenStreetBrowser, n.d.). \* Start and end of the route.

### **Driving Data and Technical Instruments**

The driving task was performed using a Nissan Leaf provided by StattAuto (StattAuto eG, 2024). Driving data was collected at high frequency via the vehicle's CAN bus (Aguiri et al., 2022) using an external custom data logger (Bernhardt, 2022). Regarding RQ1, the primary measure for ecodriving performance was the mean energy consumption (Wh) per participant, calculated as the mean of all energy steps, which were derived by multiplying motor power (in W) with the

time intervals between successive data points. A set of behavioural driving metrics supplemented the energy consumption measure for further, more differentiated analyses. Specifically, the following variables were recorded: throttle position, braking pedal pressure, and velocity (km/h). Throttle position was recorded as a percentage of pedal depression and transformed by the vehicle's internal control system into motor power output via a linear mapping function. Brake pedal pressure was recorded as a proxy for braking intensity. It represents a valid behavioural indicator, particularly during low to moderate deceleration phases, although the actual deceleration force results from a combination of regenerative braking and hydraulic braking torque. Following prior research, velocity is significantly related to energy use (Braun & Rid, 2018). Moreover, low velocity variability can indicate anticipatory driving and smooth interaction with traffic flow.

The vehicle's GPS position was recorded in decimal degrees to ensure route adherence and standardised start and end points. A dashcam recorded the front view to support sensor data verification and resolving inconsistencies if needed (e.g., GPS fallback). A smartphone (OnePlus 6) with the OsmAnd app (OsmAnd B.V., n.d.) provided turn-by-turn navigation and auditory warnings if speed limits were exceeded. The experimental setup with a data logger, dashcam, and navigation smartphone in the vehicle cockpit is shown in Figure 2.

The driving route was chronologically segmented into 11 subtracks based on speed limits to account for structural variation in situational driving demands. Thus, each subtrack represents a distinct temporal section of the drive with a constant speed limit and associated behavioural constraints. Subsequently, a self-developed web application was utilised to annotate the driving data with the specified locations and create subtracks. This process enabled the filtration and aggregation of data across these subtracks. Within each subtrack, all driving metrics were z-standardised across participants before computing the mean per metric across subtracks. This normalisation ensures that aggregated metrics reflect relative driving behaviour within each situational context and are not disproportionately influenced by scale differences introduced by the varying demands of different speed-limit zones. Aggregating raw values across the entire route without this step would risk obscuring meaningful behavioural adaptations, such as energy-saving strategies that manifest differently in low-speed versus high-speed contexts, because the degrees of behavioural freedom vary across situations. By standardising within subtracks, we equalise the diagnostic contribution of each segment and enhance the interpretability of aggregated scores. In contrast to studies that separately analyse behaviour by route types (e.g., highway vs. rural or urban vs. rural; Daun et al., 2013; Larsson & Ericsson, 2009; Staubach et al., 2014; van der Voort et al., 2001) or speed limit zones (e.g., Adell et al., 2008; Andrieu & Saint Pierre, 2012), this approach integrates the situational structure of

energy-relevant behaviour and maximises the diagnostic value of the aggregated measures across heterogeneous driving demands.

**Figure 2**

*Experimental Setup in the Cockpit of the Nissan Leaf*



*Note.* The data logger is installed on the left above the steering wheel, the dashcam is central on the windshield below the mirror, and the navigation smartphone is to the right of the steering wheel.

## **Scales and Measures**

According to common practice (Cripps, 2017), Cronbach's alpha was interpreted as poor ( $.5 \leq \alpha < .6$ ), questionable ( $.6 \leq \alpha < .7$ ), acceptable ( $.7 \leq \alpha < .8$ ), good ( $.8 \leq \alpha < .9$ ), or excellent ( $\alpha \geq .9$ ). Scales contained a 6-point Likert scale ranging from 1 (completely disagree) to 6 (completely agree).

### *Perceived Support of Action Regulation*

We employed a subjective measurement approach to evaluate the quality of information processing within action regulation, using participants' self-reports as a proxy for latent cognitive processes that are not directly measurable. In line with the definition of usability according to the ISO 9241-11 standard (International Organization for Standardization, 2018),

we define usability as the extent to which the ecodriving feedback can be used by drivers to effectively, efficiently, and satisfactorily achieve the goal of driving in an energy-efficient manner. While satisfaction generally reflects the overall positive user experience with a system, we specifically consider action confidence as the driver's sense of control. This confidence directly influences their perceived success and satisfaction in achieving energy-efficient driving goals. This factor becomes especially relevant in high-stakes, not fully automated environments, where a sense of control can significantly impact performance and user experience.

Thus, the perceived support of action regulation (see Tables A2 and A3 in Appendix A) was assessed using two perspectives: (1) usability dimensions based on ISO 9241-11 (Effectiveness, Efficiency) and action confidence, and (2) information processing stages within action regulation (Parasuraman et al., 2000; Wickens & Carswell, 2021).

From the usability perspective, three subscale means can be computed, each consisting of 5 items that relate to the information processing stages: information acquisition, information analysis, decision, and action implementation. The internal consistencies of the subscales effectiveness ( $M = 4.5$ ,  $SD = 0.9$ ,  $\alpha = .92$ ), efficiency ( $M = 4.4$ ,  $SD = 1.1$ ,  $\alpha = .95$ ) and confidence ( $M = 4.3$ ,  $SD = 1.0$ ,  $\alpha = .94$ ) were excellent, as interpreted according to Cripps (2017).

From the action regulation perspective, four subscale means are computed across three usability dimensions (effectiveness, efficiency, and confidence). The internal consistencies of the subscales information acquisition (three items,  $M = 4.4$ ,  $SD = 1.0$ ,  $\alpha = .86$ ), information analysis (six items,  $M = 4.4$ ,  $SD = 1.0$ ,  $\alpha = .93$ ), decision selection (three items,  $M = 4.4$ ,  $SD = 1.0$ ,  $\alpha = .91$ ), and action implementation (three items,  $M = 4.5$ ,  $SD = 1.0$ ,  $\alpha = .90$ ) were good to excellent.

Both perspectives provide complementary insights: the usability-oriented approach assesses how well the system supports effective, efficient, and confident action regulation, while the action regulation approach focuses on the perceived support of individual cognitive information processing stages.

#### *Perceived Support of the Mental Model within Action Regulation*

The perceived support of the *mental model* within action regulation was assessed via five items focusing on the extent to which the available information supports the *mental model* in the context of action regulation concerning the definition of *mental models* (Carroll & Olson, 1987): aspects of the system, knowing how, knowing why, expand or correct the existing *mental model*, and alignment of the *mental model* with real-world driving experiences (i.e., completeness/richness of the *mental model*). The scale's internal consistency was excellent ( $M = 4.2$ ,  $SD = 1.2$ ,  $\alpha = .90$ ).

### *Perceived Uncertainty Due to a Lack of Knowledge*

The uncertainty due to a lack of knowledge (resulting in difficulties driving energy-efficiently) was assessed via seven self-created items. Participants were informed that uncertainty was understood as resulting from a lack of knowledge, which may manifest in different ways: This could include a general lack of knowledge about energy-efficient driving strategies, uncertainty about when and how to implement specific behaviours, or a lack of understanding of why certain behaviours are considered energy-efficient. The items themselves focused on prototypical driving manoeuvres, including accelerating, braking in both high- and low-speed zones, stopping (e.g., at traffic lights or stop signs), constant-speed driving, speed selection at high speed zones, and situations requiring frequent speed adjustments (e.g., stop-and-go traffic). The internal consistency of the scale was excellent ( $M = 2.6$ ,  $SD = 1.1$ ,  $\alpha = .90$ ).

### *Ecodriving Knowledge*

Ecodriving knowledge was measured using a 5-item scale, adapted from Arend, Franke, and Stanton (2019) and previous work of the research group. The five items captured conceptually distinct but complementary facets of eco-driving knowledge, including situation-specific procedural knowledge, knowledge about using vehicle control elements, the ability to explain eco-driving strategies to others, and strategic knowledge for optimising one's driving efficiency. The scale was measured before and after the experiment. The internal consistencies of the eco-driving knowledge scale ( $M_{pre} = 3.1$ ,  $SD_{pre} = 1.3$ ,  $M_{post} = 4.2$ ,  $SD_{post} = 1.0$ ) were excellent ( $\alpha_{pre} = .95$ ,  $\alpha_{post} = .92$ ). Gain in perceived eco-driving knowledge was calculated by subtracting participants' pre-experiment mean scores from their post-experiment mean scores ( $M_{post-pre} = 1.1$ ,  $SD_{post-pre} = 1.2$ ).

### **Ecodriving Tips**

In the first part of the study, tips on energy-efficient driving were formulated. For this purpose, based on the study by Sureth et al. (2019), the manuals of common EV manufacturers were first searched for rules of behaviour or tips on eco-driving. The vehicle models that recorded the most new registrations in the current year and for which the manuals were freely accessible were included: Tesla Model Y (Tesla, 2024b) and Model 3 (Tesla, 2024a), MG4 (MG, 2022), Škoda Enyaq (Škoda, 2024), Fiat 500e (Fiat, 2019), Dacia Spring (Dacia, 2024) and Volvo EX40 (Volvo, 2024). The manual for the Nissan Leaf was also included, as this vehicle was used in the study (Nissan, 2024). Based on technical system knowledge about BEVs, which was gained from the manuals and the knowledge of the experts involved, and taking into account the tips from the study by Sureth et al. (2019), specific tips for various driving manoeuvres were developed. The tips were less detailed and comprehensive than those in Sureth et al. (2019), but were based on

the tips developed there and verified against the technical information in the BEV manuals. Then, a total of five experts from the fields of electromobility and engineering psychology, with an average of 9.8 years of professional experience, were involved. These experts assessed and refined the initial drafts of the tips in several correction loops concerning their practical suitability and technical accuracy.

The corrections resulted in a final set of seven ecodriving tips for BEVs, which were compiled in two different formulation variants (see Table 1 for the English version and Table A1 in Appendix A for the German version). The first formulation variant was a standard, context-free formulation commonly used in vehicle manuals and thus represents the current standard. The second formulation was formulated analogously to Sureth et al. (2019) with the inclusion of *know-how* and *know-why* as implementation intentions, i.e., they contained both a description of what must be done with the vehicle control system in which situation (“if...”) and a technical justification of why this behaviour is maximally energy-efficient.

**Table 1**

*Tips for Seven Driving Manoeuvres*

Manoeuvre	Generic	Know-how-and-why
Accelerating	Accelerate moderately.	If you want to accelerate from a standstill or to higher speeds, then press the accelerator pedal constantly and moderately until you have reached your desired speed. This allows you to achieve an optimum ratio of speed gain to energy consumption, and the electric motor is therefore at optimum efficiency. This optimum degree of acceleration in an electric car may differ from what you are familiar with from a combustion engine vehicle.
Braking: mechanical braking	Brake early and avoid hard braking.	If you want to reduce your speed, then avoid pressing down hard on the brake pedal and using the mechanical brake. If you press harder on the brake pedal, the mechanical brake is activated in addition to recuperation. As a result, the momentum energy is ultimately converted into heat and is therefore completely lost.
Braking: higher speed zone	Brake lightly in the high-speed zone (> 60 km/h).	If you want to reduce your speed in the high speed range (from 60 km/h), then first press the brake pedal lightly so that you recuperate. Recuperation allows at least part of the momentum energy to be temporarily stored in the battery. Especially at high speeds, the distance to coast in neutral is very long, and you should therefore first use recuperation to reduce speed until you are in the low speed range.
Braking: low speed zone	At lower speeds (or if light braking is too strong), engage neutral gliding.	If you want to reduce your speed at low speeds or if you notice that you are coming to a standstill too early with recuperation, then try to coast in neutral by easing off the accelerator pedal far enough so that neither energy is consumed nor recovered. You should avoid actively using recuperation at lower speeds, as conversion losses occur when storing momentum energy (kinetic energy) in the battery, and only part of the momentum can actually be temporarily stored.

**Table 1** (continued)

Manoeuvre	Generic	Know-how-and-why
Constant speed: neutral gliding	Try to coast in neutral as often as possible.	If you drive at constant speed (little traffic), then try to maintain neutral gliding as often as possible (without recuperation) by easing off the accelerator pedal to such an extent that neither energy is consumed nor recovered. Alternate this with constant, moderate acceleration so that you achieve your desired speed on average. It is most efficient to coast in neutral, as the kinetic energy once built up is optimally utilised for propulsion, as further conversion losses during recuperation and acceleration are avoided. By alternating between gliding in neutral and moderate acceleration, the advantage of neutral gliding is utilised, and speed is best maintained by accelerating in the optimum range.
Speed changes / stop and go	Avoid accelerating unnecessarily or 'braking away' previously built-up speed (momentum).	If you have to adjust your speed frequently (e.g., stop and go or before a bend), then drive at a constant low speed by anticipating as much as possible so that you neither accelerate unnecessarily nor 'brake away' the speed (momentum) you have built up. Every acceleration (building up momentum) costs energy. You can therefore save energy by not building up kinetic energy that you do not necessarily need in the first place. Every time you reduce speed, previously built-up kinetic energy (momentum) is lost.
Speed selection / Higher speed zone	Keep your speed as low as possible in the high-speed zone.	If you are travelling on roads with a speed limit of 60 km/h or higher, then keep your speed as low as possible. At high speeds, energy consumption is mainly determined by air resistance, as this increases quadratically - i.e., disproportionately - with travelling speed. This leads to correspondingly high energy losses.

## 7.5. Results

For all analyses, the threshold of  $\alpha$  was set to .05 and effect sizes were interpreted according to Bühner (2011) and Cohen (1988, 1992). Small effects were defined as  $\eta^2 = \epsilon^2 = .01$ ,  $V = r = .10$ , and  $d = 0.20$ ; moderate effects as  $\eta^2 = \epsilon^2 = .06$ ,  $V = r = .30$ , and  $d = 0.50$ ; and large effects as  $\eta^2 = \epsilon^2 = .14$ ,  $V = r = .50$ , and  $d = 0.80$ . Epsilon squared ( $\epsilon^2$ ) was chosen and calculated based on Tomczak and Tomczak (2014) as a common approach for the Kruskal–Wallis test. Statistical assumptions for the applied parametric tests were evaluated prior to analysis. Normality of residuals was assessed using the Shapiro–Wilk test (Shapiro & Wilk, 1965), homogeneity of variances using Levene's test (Levene, 1960), and homoscedasticity using the Breusch–Pagan test (Breusch & Pagan, 1979). In case of violated assumptions of the ANOVA, non-parametric alternatives were used: the Kruskal–Wallis test (Kruskal & Wallis, 1952) for continuous variables and Pearson's chi-square test (Agresti, 2007; Pearson, 1900) for categorical variables.

To test **H1–H5**, we primarily applied contrast analyses, which allow for more precise hypothesis testing than omnibus  $F$ -tests such as ANOVA (Buckless & Ravenscroft, 1990; Wiens & Nilsson, 2017). We followed the recommended steps for contrast analysis outlined by Rosenthal et al. (2000). All analyses were performed in R (R Core Team, 2024) using RStudio (Posit Team, 2025).

The R packages *stats* (R Core Team, 2024), *emmeans* (Lenth, 2024), *rstatix* (Kassambara, 2023), *car* (Fox & Weisberg, 2024) and *cofad* (Titz & Burkhardt, 2021, 2024) were used, amongst others.

As shown in Table 2, the three groups did not significantly differ regarding the total driving experience with every kind of vehicle (km), the total driving experience with BEV (km), age, gender, education level, ecodriving motivation (Arend & Franke, 2017), ecodriving knowledge before participating, or ATI (Franke et al., 2019). This suggests that the groups were comparable with no strong biases in sample composition.

**Table 2**

*Analysis of Group Differences in Sample Composition*

Variable	Test	Statistic	$p$	$\epsilon^2$	$\eta^2$	$V$
Total driving experience across all vehicles (km)	Kruskal–Wallis	$H(2)$	0.86	.649	.02	
Total driving experience with BEV (km)	Kruskal–Wallis	$H(2)$	0.76	.684	.04	
Age	Kruskal–Wallis	$H(2)$	0.94	.624	.02	
Gender	Chi-square	$\chi^2(4)$	2.17	.705		.15
Education Level	Chi-square	$\chi^2(10)$	8.29	.601		.29
Ecodriving motivation	ANOVA	$F(2, 47)$	0.08	.927	<.01	
Technical background knowledge	ANOVA	$F(2, 47)$	2.85	.068		.11
Affinity for technology interaction (ATI)	ANOVA	$F(2, 47)$	0.37	.692		.02

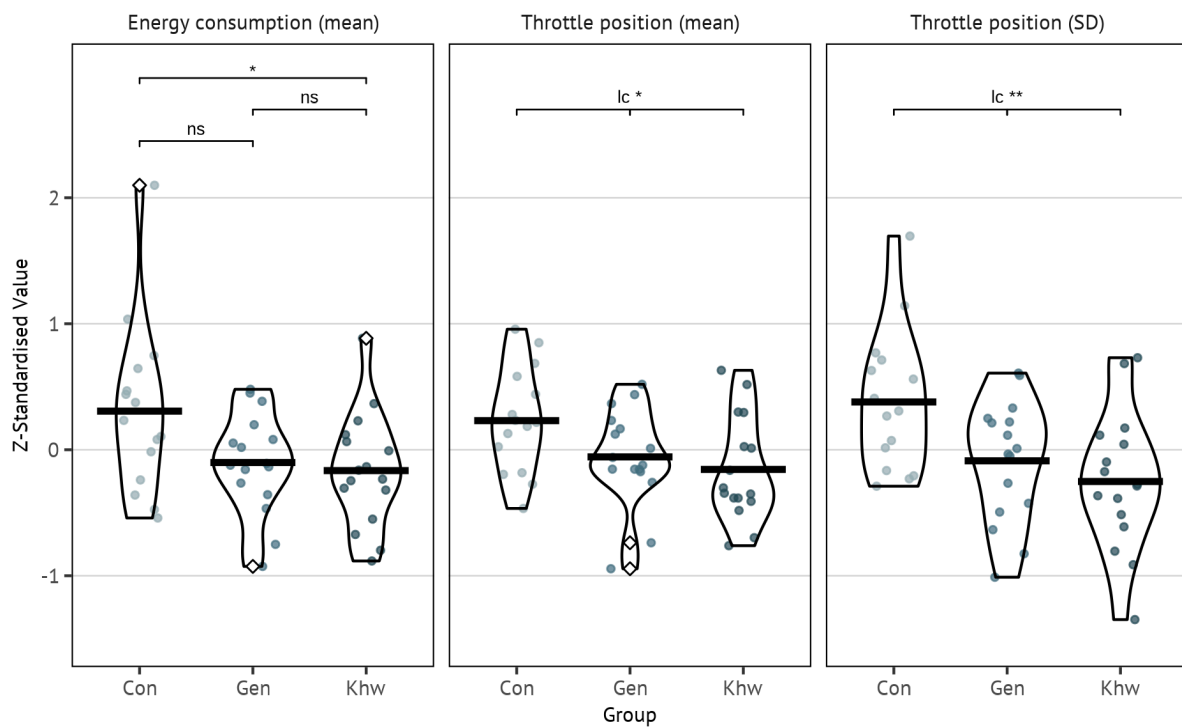
Note.  $n_{control} = 16$ ,  $n_{generic} = 16$ ,  $n_{know-how-and-why} = 18$ .

### Effects on Ecodriving Performance (RQ1)

Contrast analyses were performed to test the hypothesis that participants in the *know-how-and-why* condition will demonstrate the best ecodriving performance, followed by those in the *generic* condition, with participants in the *control* condition showing the lowest performance. We assigned contrast weights based on group (*control* = 1.5, *generic* = -0.5, *know-how-and-why* = -1), to reflect the hypothesised gradient in explanatory depth of the feedback conditions. All descriptive and inferential statistics related to driving performance are reported in Table B1 in Appendix B. Due to space constraints, only statistically significant contrasts are visualised in Figure 3.

Figure 3

Ecodriving Performance Regarding Z-Standardised Energy Consumption (Mean) and Throttle Position (Mean, SD)



Note. The solid lines represent the group-specific means. Outliers, defined as values more than  $1.5 \times \text{IQR}$  below  $Q_1$  or above  $Q_3$ , are indicated by white diamonds. \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ , ns = not significant, lc = linear contrast. Con = control, Gen = generic, Khw = know-how-and-why.  $n_{\text{control}} = 15$ ,  $n_{\text{generic}} = 16$ ,  $n_{\text{know-how-and-why}} = 16$ .

A significant contrast was observed for the z-standardised **mean energy consumption**,  $F(1, 44) = 4.18$ ,  $p = .047$ ,  $r = .28$  (small-to-moderate effect). Mean energy consumption was highest in the *control* group ( $M = 0.3$ ,  $SD = 0.7$ ), followed by the *generic* ( $M = -0.1$ ,  $SD = 0.4$ ) and *know-how-and-why* ( $M = -0.2$ ,  $SD = 0.5$ ) groups. Based on the raw energy consumption values in Wh, mean consumption in the *control* group ( $M = 538.9$ ,  $SD = 106.3$ ) was 11.3% higher than in the *know-how-and-why* group ( $M = 484.1$ ,  $SD = 71.6$ ).

Furthermore, a significant contrast was observed for the z-standardised **standard deviation of velocity**,  $F(1, 44) = 5.48$ ,  $p = .024$ ,  $r = .33$  (moderate effect). The highest variability occurred in the *control* group ( $M = 0.2$ ,  $SD = 0.3$ ), followed by the *generic* ( $M = -0.1$ ,  $SD = 0.4$ ) and *know-how-and-why* ( $M = -0.1$ ,  $SD = 0.3$ ) groups. Moreover, a significant contrast was observed for the **z-standardised mean throttle position**,  $F(1, 44) = 7.47$ ,  $p = .009$ ,  $r = .38$  (moderate effect). As visualised in Figure 3, throttle position was highest in the *control* group ( $M = 0.2$ ,  $SD = 0.4$ ), followed by the *generic* ( $M = -0.1$ ,  $SD = 0.4$ ) and *know-how-and-why* ( $M = -0.2$ ,  $SD = 0.4$ ) groups.

A further significant contrast emerged for the z-standardised **standard deviation of throttle position**,  $F(1, 44) = 11.69$ ,  $p = .001$ ,  $r = .46$  (moderate effect). The highest variability occurred in the *control* group ( $M = 0.4$ ,  $SD = 0.6$ ), with lower levels in the *generic* ( $M = -0.1$ ,  $SD = 0.5$ ) and *know-how-and-why* ( $M = -0.3$ ,  $SD = 0.5$ ) groups.

No significant contrasts were found for any of the following z-standardised metrics ( $ps > .05$ ), with small to moderate effect sizes ( $|r| = .01-.27$ ): mean, median, and SD of braking pedal pressure; median throttle position; as well as mean and median of velocity.

Overall, **H1** is partially supported: Significant linear contrasts for mean energy consumption, velocity variability, and both the mean and variability of throttle position fully support the hypothesis. However, no significant linear contrasts were found for mean and median velocity or brake pedal pressure.

### Effect on Action Regulation Quality (RQ2)

A series of linear contrasts was conducted to test the hypotheses. The hypotheses **H2**, **H3**, and **H5** proposed that the *know-how-and-why* group would achieve higher scores compared to the *control* group and the *generic* group. Thus, we assigned the following contrast weights based on groups: *control* = -1.5, *generic* = 0.5, *know-how-and-why* = 1. This contrast reflects the assumption that tips improve outcomes relative to no information and that know-how-and-why tips are more effective than compact generic tips. Regarding **H4**, the *know-how-and-why* group should achieve the lowest scores of perceived uncertainty due to a lack of knowledge, and the *control* group the highest. Thus, we assigned contrast weights with *control* = 1.5, *generic* = -0.5, and *know-how-and-why* = -1. An overview of both descriptive and inferential statistics for the subjective measures can be found in Table B2 in Appendix B.

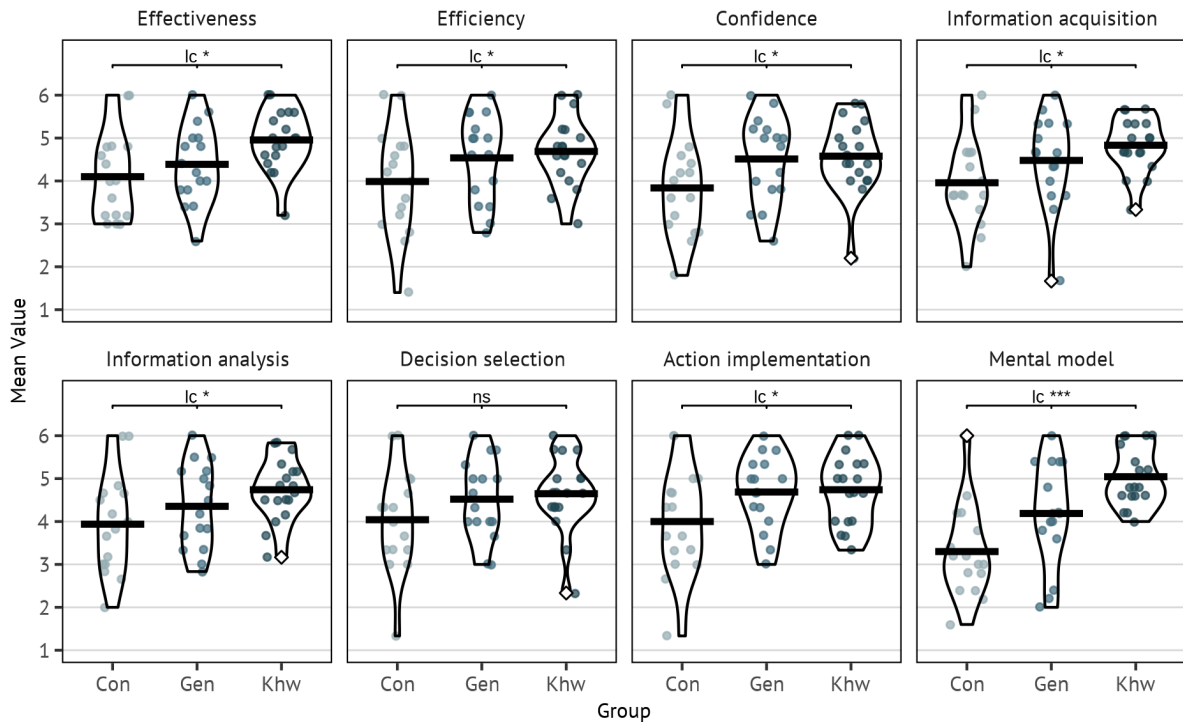
#### *Perceived Support of Action Regulation Concerning Usability Dimensions (H2)*

As visualised in Figure 4, the results showed a significant linear contrast regarding perceived support of effectiveness within action regulation,  $F(1, 47) = 6.02$ ,  $p = .018$ ,  $r = .34$  (moderate effect). Participants in the *know-how-and-why* group ( $M = 5.0$ ,  $SD = 0.7$ ) rated perceived support of **effective** action regulation significantly higher than those in the *generic* group ( $M = 4.4$ ,  $SD = 0.9$ ), with the lowest ratings in the *control* group ( $M = 4.1$ ,  $SD = 1.0$ ). Significant linear contrasts were also observed for perceived **efficiency**,  $F(1, 47) = 4.20$ ,  $p = .046$ ,  $r = .29$ , and **confidence**,  $F(1, 47) = 5.37$ ,  $p = .025$ ,  $r = .32$  (moderate effects). In both cases, participants in the *know-how-and-why* group reported higher perceived support ( $M = 4.7$ ,  $SD = 0.8$  for efficiency;  $M = 4.6$ ,  $SD = 0.9$  for confidence) compared to the *generic* ( $M = 4.5$ ,  $SD = 1.0$  and  $M = 4.5$ ,  $SD = 1.0$ )

and *control* groups ( $M = 4.4, SD = 1.2$  and  $M = 4.0, SD = 1.2$ ), respectively. Overall, the findings fully support **H2**.

**Figure 4**

*Perceived Support of Effective Action Regulation, Information Acquisition, Information Analysis, and the Mental Model*



*Note.* The solid lines represent the group-specific means. Outliers, defined as values more than  $1.5 \times IQR$  below  $Q_1$  or above  $Q_3$ , are indicated by white diamonds. \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .01$ , lc = linear contrast, ns = not significant. Con = Control, Gen = Generic, Khw = Know-how-and-why.  $n_{control} = 16$ ,  $n_{generic} = 16$ ,  $n_{know-how-and-why} = 18$ .

*Perceived Support of Action Regulation Concerning Information Processing Stages (H3)*

As visualised in Figure 4, a significant linear contrast was found for perceived support of **information acquisition**,  $F(1, 47) = 6.99, p = .011, r = .37$  (moderate effect). The *know-how-and-why* group reported the highest perceived support of information acquisition ( $M = 4.8, SD = 0.6$ ), the *control* group the lowest ( $M = 4.0, SD = 1.0$ ) and the *generic* group fell in between ( $M = 4.5, SD = 1.1$ ). Similarly, a significant linear contrast was found for perceived support of **information analysis**,  $F(1, 47) = 5.16, p = .028, r = .32$  (moderate effect). The *know-how-and-why* group reported the highest perceived support of information analysis ( $M = 4.7, SD = 0.7$ ), the *control* group the lowest ( $M = 3.9, SD = 1.2$ ), and the *generic* group fell in

between ( $M = 4.4$ ,  $SD = 1.0$ ). A significant linear contrast was also found for perceived support of **action implementation**,  $F(1, 47) = 5.65$ ,  $p = .022$ ,  $r = .33$  (moderate effect). Participants in the *know-how-and-why* group reported the highest perceived support ( $M = 4.7$ ,  $SD = 0.8$ ), followed by the *generic* group ( $M = 4.7$ ,  $SD = 0.9$ ), with the lowest ratings in the *control* group ( $M = 4.0$ ,  $SD = 1.2$ ). No significant linear contrast was found for perceived support of **decision selection**,  $F(1, 47) = 3.33$ ,  $p = .074$ ,  $r = .26$  (small effect).

Overall, the results largely support **H3**, as the *know-how-and-why* group reported the highest perceived support across most information processing stages.

#### *Perceived Support of the Mental Model within Action Regulation (H4)*

As shown in Figure 4, there was a significant linear contrast for perceived support of the *mental model*,  $F(1, 47) = 21.98$ ,  $p < .001$ ,  $r = .56$  (large effect). The *know-how-and-why* group ( $M = 5.0$ ,  $SD = 0.7$ ) reported the highest perceived support of the *mental model*, the *control* group the lowest ( $M = 3.3$ ,  $SD = 1.1$ ), and the *generic* group fell in between ( $M = 4.2$ ,  $SD = 1.2$ ). This finding fully supports **H4**.

#### *Perceived Uncertainty Due to a Lack of Knowledge (H5)*

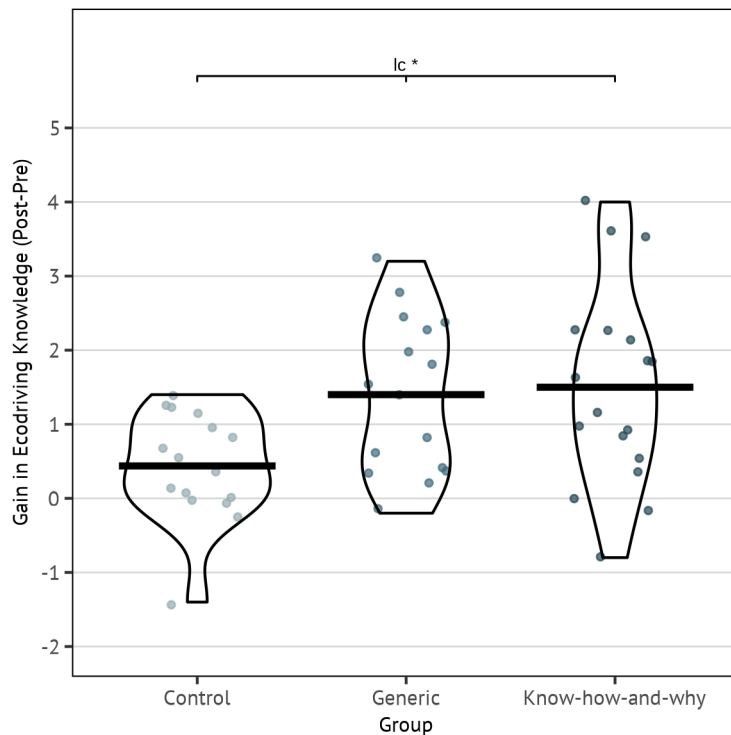
There was no significant linear contrast for perceived uncertainty due to a lack of knowledge,  $F(1, 47) = 2.26$ ,  $p = .139$ ,  $r = .22$  (small effect). Thus, **H5** is not supported.

#### **Effect on Gain in Perceived Ecodriving Knowledge (RQ3, H6)**

Regarding the gain in perceived ecodriving knowledge, the *know-how-and-why* group would achieve the highest scores, and the *control* group the lowest. Thus, we assigned contrast weights based on groups with *control* =  $-1.5$ , *generic* =  $0.5$ , and *know-how-and-why* =  $1$ . There was a significant linear contrast,  $F(1, 47) = 9.95$ ,  $p = .003$ ,  $r = .41$  (moderate effect). As visualised in Figure 5, the gain in perceived ecodriving knowledge was highest in the *know-how-and-why* group ( $M = 1.5$ ,  $SD = 1.3$ ), lowest in the *control* group ( $M = 0.4$ ,  $SD = 0.7$ ), and the *generic* group fell in between ( $M = 1.4$ ,  $SD = 1.1$ ). Thus, **H6** is fully supported.

Figure 5

Gain in Perceived Ecodriving Knowledge



Note. The solid lines represent the group-specific means. \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ , lc = linear contrast.  $n_{control} = 16$ ,  $n_{generic} = 16$ ,  $n_{know-how-and-why} = 18$ .

## 7.6. Discussion

### Summary of Results

This study examined the effects of psychologically comprehensive tips integrating action guidance with explanatory rationale (know-how-and-why) versus compact generic tips on drivers' subjective perceptions of action regulation and their actual ecodriving performance in a BEV.

Partially in line with **H1**, linear contrasts revealed significant effects in driving data for mean energy consumption, mean throttle position, throttle position variability, and velocity variability. The contrast pattern indicated a linear decrease across groups, with the *know-how-and-why* group showing the lowest means and standard deviations. These findings suggest that structured ecodriving tips can promote more stable and controlled driving behaviours,

contributing to energy efficiency. Notably, linear contrasts of other metrics, such as braking pedal pressure, did not reach significance, indicating potential boundaries of immediate behavioural adaptation or the need for extended practice to impact those dimensions. Explanatory formulations may be particularly effective in promoting certain aspects of energy-efficient driving behaviour.

Mostly in line with **H2** and **H3**, participants in the *know-how-and-why* group reported the highest perceived support of action regulation across all usability dimensions and most information processing stages (information acquisition, information analysis, action implementation). Contrary to **H3**, there was no significant linear contrast for the perceived support of decision selection.

**H4** can be fully accepted, as the *know-how-and-why* group showed the highest perceived support of the *mental model*, and the *control* group the lowest. **H5** has to be rejected, as there was no significant linear contrast regarding perceived uncertainty due to a lack of knowledge. In line with **H6**, the gain in perceived ecodriving knowledge was highest in the *know-how-and-why* group and lowest in the *control* group.

Taken together, these findings suggest that structured, explanatory ecodriving information can enhance both perceived and actual support for energy-efficient driving—particularly in terms of perceived support of action regulation and the *mental model*, higher gain in ecodriving knowledge, reduced energy consumption, reduced mean and variability of throttle position, and reduced velocity variability. Explanatory know-how-and-why tips appeared especially effective in influencing drivers' experience and specific driving performance outcomes. However, the absence of several significant contrasts, such as braking pedal pressure, indicates that some components of adaptive driving may require more intensive training, repeated exposure, or experiential learning to be effectively influenced.

## Implications

These findings contribute to a more differentiated understanding of how text-based interventions can support energy-efficient behaviour in BEVs. Specifically, the study supports previous research suggesting that the combination of *know-how* and *know-why* can be more effective than generic advice (Sureth et al., 2019). Importantly, it extends this insight to BEVs, where drivers must manage less intuitive energy dynamics compared to ICEVs and benefit from support in forming structured mental representations (Neumann & Krems, 2016). The observed advantage in perceived support of the *mental model* within action regulation underscores the cognitive relevance of well-designed information formats that help drivers integrate input–output relationships and system understanding into their behaviour.

The effectiveness of the know-how-and-why tips appears to be linked to their informational content and their structural design. The use of if-then-why formulations likely enhanced drivers' ability to attend to relevant situational cues in the information acquisition stage (in line with Achtziger et al., 2012) and to simulate the consequences of specific manoeuvres mentally in the information analysis stage.

One possible explanation for the null findings regarding the support of decision selection may be that deeper behavioural adaptation may require more than one-time informational input. Decision selection likely benefits from repeated experience, transfer and feedback in various driving situations, particularly in unfamiliar vehicle systems. For novice BEV drivers, repeated practice and contextualised feedback may be essential to translate mental representations into action.

The observed linear trend with the lowest mean energy consumption in the *know-how-and-why* group expands earlier findings showing that even generic textual ecodriving interventions or explanations of efficiency-relevant behaviours can lead to measurable improvements in driving efficiency (Andrieu & Saint Pierre, 2012; Azzi et al., 2011; Beloufa et al., 2019; Günther et al., 2019; van der Voort et al., 2001). Specifically, the present study implemented systematically derived, psychologically grounded tips specifically tailored to the energy dynamics of BEVs. In contrast to prior studies such as Sureth et al. (2019), which primarily focused on energy consumption of HEVs, the current study tested a structured intervention with a BEV, included less experienced drivers, and captured a broader set of performance indicators such as throttle position and variability. This extension demonstrates that explanatory interventions can foster not only subjective understanding but also observable behavioural adaptation in the context of BEV.

From a practical perspective, the findings point to clear implications for the design of ecodriving interventions. Practitioners should prioritise profound formats that combine *know-how* and *know-why* and present this information in cognitively supportive structures. Implementation in onboarding routines, training programs, or in-vehicle interfaces should avoid abstract or decontextualised tips and instead deliver targeted, situation-aware guidance. The observed reductions in energy consumption, throttle and velocity variability further underscore the potential of structured textual interventions to improve not only perceived support but also real driving behaviour in BEVs.

Integrating such interventions with experiential formats, such as simulator training or real-time feedback systems, could strengthen behavioural internalisation and long-term effectiveness. Overall, the study highlights that successful ecodriving interventions in BEVs are not merely a matter of providing information but of aligning that information with the cognitive needs of

action regulation. Supporting drivers in perceiving, understanding, and applying energy-efficient strategies requires both informative content and structured delivery tailored to the psychological demands of BEV driving.

### **Limitations and Future Work**

While the present study provides valuable insights into the effects of differently structured ecodriving tips on subjective aspects of action regulation and *mental model* support, its findings should be interpreted in light of some methodological limitations. Most notably, the relatively small sample size ( $N = 50$  for subjective scales,  $N' = 47$  for driving data), distributed across three between-subjects conditions, limited the statistical power to detect small-to-medium effects. Therefore, it is possible that some meaningful group differences were not detected. Future research would benefit from larger samples, particularly when employing between-subjects designs.

In addition, the driving task was relatively short, averaging 11.0 kilometres and approximately 21.8 minutes. This limited exposure may have reduced the likelihood that participants encountered a sufficient variety of situations to apply the recommended strategies. Ecodriving behaviours such as neutral gliding, regenerative braking, or anticipatory acceleration are often context-dependent and may not have been consistently relevant or observable within the route or timeframe. Furthermore, previous research indicates that drivers often require several months to develop ecodriving strategies (Franke et al., 2017), and performance improvements may be even larger several months after ecodriving training (Sullman et al., 2015).

As is typical in field studies, additional sources of variability, such as traffic flow or technical disruptions, could not be fully controlled. For instance, a few participants reported issues with the phone mount used for navigation, which may have interfered with their ability to maintain focus. Future implementations should aim to reduce such variability through standardised equipment and more controlled conditions where feasible.

Moreover, because the study focused on immediate subjective responses following a single exposure to the intervention, it does not offer insights into the durability or longer-term development of *mental models*, perceived knowledge, or action confidence. Prior work suggests that newly formed representations may deteriorate over time without reinforcement through practice or repeated exposure (Hiraoka et al., 2011; Jamson et al., 2015). This suggests that short-term interventions may underestimate the full potential of behavioural change. At the same time, studies with follow-up measurements after two to 12 months demonstrate that the initial reductions in fuel consumption tend to diminish over time (af Wåhlberg, 2007; Geiler & Kerwien, 2008; Savković et al., 2020; Wu et al., 2015; Zarkadoula et al., 2007), highlighting the

challenge of sustaining ecodriving behaviour without continued reinforcement. Thus, the improvements observed in perceived support may reflect short-term effects that are not sustained. Future studies should incorporate longitudinal assessments and repeated interactions with the intervention to examine whether initial gains persist and translate into behavioural adaptation.

Beyond increasing the duration or repetition of interventions, future research should also aim to expand the set of driving metrics analysed. While the current study focused on energy consumption, throttle position, braking pedal pressure, and velocity, more granular behaviourally anchored metrics, such as the proportion of time spent in regenerative braking, mechanical braking, or neutral gliding, could offer deeper insight into how specific driving strategies are implemented. In addition, positive and negative longitudinal acceleration may help assess whether interventions affect distinct driving manoeuvres differently. Such metrics would more directly reflect the intended behavioural targets of the intervention and better capture subtle patterns of adaptation.

In sum, the study demonstrates promising effects of structured ecodriving information on drivers' perceived support of action regulation, ecodriving knowledge and *mental model* support. The results provide a valuable foundation for future research using longer study durations, repeated measures, larger sample sizes, and multimodal assessments to better understand how structured interventions shape sustainable driving behaviour over time.

## 7.7. Conclusion

This study underscores the importance of not only what information is provided to drivers but also how that information is cognitively structured and embedded in support of action regulation. Psychologically comprehensive ecodriving tips that integrate strategies and their technical rationale can enhance drivers' perceived ability to process relevant cues, analyse energy-related information, implement and control their behaviour effectively, efficiently, and confidently, and support the *mental model* necessary for energy-efficient driving. The findings point to the value of structured interventions that align with the cognitive demands of the driving task. Importantly, these subjective effects were mirrored by objective improvements in driving behaviour. Linear contrasts revealed significant effects for mean energy consumption, velocity variability, as well as for the mean and variability of throttle position. The observed pattern indicates a linear trend across groups, with the *know-how-and-why* group showing the most energy-efficient and smooth driving behaviour. These findings highlight the behavioural relevance of well-designed informational support.

Beyond its substantive findings, the study contributes methodologically by differentiating perceived support of action regulation across two complementary perspectives: usability dimensions and information processing stages. Additionally, conceptualising and measuring perceived support of the *mental model* within action regulation as a distinct construct offers a more differentiated understanding of how informational interventions shape drivers' comprehension of system behaviour. This approach allows for a more theory-driven evaluation of how different aspects of support map onto cognitive demands during ecodriving.

To achieve broader and more durable behavioural change, future ecodriving studies should combine structured explanatory content with repeated exposure and experiential formats that reinforce system understanding and adaptive strategy use over time.

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## 7.10. Appendix

### Appendix A: Experimental Material and Scales

**Table A1**

*Tip Formulations for Seven Driving Manoeuvres in German*

Generic	Know-how-and-why
Beschleunigen Sie moderat.	Wenn Sie aus dem Stand oder auf höhere Geschwindigkeiten beschleunigen möchten, dann drücken Sie das Fahrpedal konstant und moderat, bis Sie Ihre Wunschgeschwindigkeit erreicht haben. Dadurch erreichen Sie ein optimales Verhältnis des Geschwindigkeitsgewinns pro Energieverbrauch und der Elektromotor befindet sich somit im optimalen Wirkungsgrad. Dieser optimale Beschleunigungsgrad beim Elektroauto weicht möglicherweise von dem ab, was Sie vom Verbrennerfahrzeug kennen.
Bremsen Sie frühzeitig und vermeiden Sie starkes Bremsen.	Wenn Sie Ihre Geschwindigkeit verringern wollen, dann vermeiden Sie es möglichst, das Bremspedal stark zu drücken und so die mechanische Bremse zu verwenden. Bei stärkerem Druck auf das Bremspedal wird zusätzlich zur Rekuperation die mechanische Bremse aktiviert. Damit wird die Schwungenergie letztendlich in Wärme umgewandelt und geht somit vollständig verloren.
Bremsen Sie im hohen Geschwindigkeitsbereich (ab 60km/h) leicht.	Wenn Sie im hohen Geschwindigkeitsbereich (ab 60 km/h) Ihre Geschwindigkeit verringern wollen, dann drücken Sie zunächst das Bremspedal leicht, so dass Sie rekuperieren. Mit der Rekuperation kann zumindest ein Teil der abzubauenen Schwungenergie in die Batterie zwischengespeichert werden. Gerade bei hohen Geschwindigkeiten ist die Strecke zum Ausrollen im Neutralbereich sehr lang und Sie sollten daher zunächst Geschwindigkeit mit der Rekuperation abbauen, bis Sie im niedrigen Geschwindigkeitsbereich sind.
Bei niedrigeren Geschwindigkeiten (oder wenn leichte Bremsung zu stark ist), gleiten Sie im Neutralbereich.	Wenn Sie bei niedrigen Geschwindigkeiten fahren oder bemerken, mit Rekuperation zu früh zum Stillstand zu kommen, dann versuchen Sie im Neutralbereich zu gleiten, indem Sie so weit vom Gaspedal gehen, dass weder Energie verbraucht, noch zurückgewonnen wird. Das aktive Einsetzen der Rekuperation bei niedrigeren Geschwindigkeiten sollten Sie vermeiden, da es bei der Speicherung von Schwungenergie (Bewegungsenergie) in die Batterie zu Umwandlungsverlusten kommt und so nur ein Teil des Schwungs wirklich zwischengespeichert werden kann.
Versuchen Sie möglichst oft im Neutralbereich zu gleiten.	Wenn Sie freie Fahrt haben, dann versuchen Sie möglichst oft im Neutralbereich (ohne Rekuperation) zu gleiten, indem Sie so weit vom Gaspedal gehen, dass weder Energie verbraucht noch zurückgewonnen wird. Dies wechseln Sie mit konstanten, moderaten Beschleunigungen ab, sodass Sie im Durchschnitt Ihre gewünschte Geschwindigkeit erzielen. Am effizientesten ist es im Neutralbereich zu gleiten, da hierbei die einmal aufgebaute kinetische Energie optimal zur Fortbewegung genutzt wird, da weitere Umwandlungsverluste beim Rekuperieren und Beschleunigen vermieden werden. Durch den Wechsel zwischen Gleiten im Neutralbereich und moderaten Beschleunigungen nutzt man den Vorteil des neutralen Gleitens und hält durch Beschleunigungen im Optimalbereich die Geschwindigkeit am besten aufrecht.
Vermeiden Sie es unnötig zu beschleunigen oder zuvor aufgebaute Geschwindigkeit (Schwung) "wegzubremsen".	Wenn Sie Ihre Geschwindigkeit häufig anpassen müssen (z.B. Stop and Go oder vor einer Kurve), dann fahren Sie durch vorausschauendes Fahren möglichst mit konstanter niedriger Geschwindigkeit, sodass Sie weder unnötig beschleunigen noch Ihre aufgebaute Geschwindigkeit (Schwung) "wegbremsen". Jede Beschleunigung (Aufbau von Schwung) kostet Energie. Daher können Sie besonders dadurch Energie sparen, dass Sie Bewegungsenergie, die Sie nicht unbedingt brauchen, erst gar nicht aufbauen. Bei jedem Abbau von Geschwindigkeit geht vorher aufgebaute Bewegungsenergie (Schwung) verloren.

**Table A1** (continued)

Halten Sie im hohen Geschwindigkeitsbereich Ihre Geschwindigkeit so niedrig wie möglich.	Wenn Sie auf Straßen mit einem Tempolimit von 60 km/h oder höher fahren, dann halten Sie Ihre Geschwindigkeit so niedrig wie möglich. Bei hohen Geschwindigkeiten wird der Energieverbrauch hauptsächlich durch den Luftwiderstand bestimmt, da dieser quadratisch - also überproportional stark - mit der Fahrgeschwindigkeit ansteigt. Dies führt entsprechend zu starken Energieverlusten.
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**Table A2**

*Perceived Support of Action Regulation Scale in German*

Items	Usability	Information processing
... kann ich alle relevanten Informationen genau wahrnehmen.	1	Acq
... kann ich präzise feststellen, ob ich im Hinblick auf mein Ziel bestmöglich handle.	1	Ana
... kann ich Handlungsmöglichkeiten und deren Auswirkungen genau ableiten.	1	Ana
... kann ich optimal entscheiden, wie ich mein Handeln im Hinblick auf mein Ziel anzupassen habe.	1	Dec
... kann ich mein Handeln bestmöglich im Hinblick auf mein Ziel umsetzen.	1	Imp
... kann ich alle relevanten Informationen mühelos wahrnehmen.	2	Acq
... kann ich ohne Anstrengung feststellen, ob ich im Hinblick auf mein Ziel bestmöglich handle.	2	Ana
... kann ich Handlungsmöglichkeiten und deren Auswirkungen mühelos ableiten.	2	Ana
... kann ich schnell entscheiden, wie ich mein Handeln im Hinblick auf mein Ziel anzupassen habe.	2	Dec
... kann ich mein Handeln mühelos im Hinblick auf mein Ziel umsetzen.	2	Imp
... bin ich mir sicher, dass ich alle relevanten Informationen einbezogen habe, um mein Verhalten zu verbessern.	3	Acq
... fühle ich mich sicher dabei festzustellen, ob ich im Hinblick auf mein Ziel bestmöglich handle.	3	Ana
... fühle ich mich sicher, Handlungsmöglichkeiten und deren Auswirkungen abzuleiten.	3	Ana
... kann ich sicher entscheiden, wie ich mein Handeln im Hinblick auf mein Ziel anzupassen habe.	3	Dec
... fühle ich mich sicher darin, mein Handeln bestmöglich im Hinblick auf mein Ziel anzupassen.	3	Imp

*Note.* 1 = effectiveness, 2 = efficiency, 3 = confidence, Acq = information acquisition, Ana = information analysis, Dec = decision selection, Imp = action implementation. Instruction text: "Während Sie versuchen, möglichst energieeffizient zu fahren (= Ziel), können verschiedene kognitive Prozesse eine Rolle spielen, wie: auf relevante Informationen aus dem Fahrzeug oder der Umwelt achten; Kontrollieren, erkennen und verstehen, wie das Handeln vom Ziel abweicht; Handlungsmöglichkeiten ableiten und deren Vor- und Nachteile abwägen; für die optimale Handlungsmöglichkeit entscheiden und sie umsetzen. Zunächst geht es darum, wie [gut bzw. genau / mühelos / sicher] Sie das Ziel, energieeffizient zu fahren, mithilfe der verfügbaren Informationen erreichen konnten. Mit "verfügbaren Informationen" meinen wir [...]. Bitte geben Sie den Grad Ihrer Zustimmung zu folgenden Aussagen an. Mithilfe der verfügbaren Informationen..."

**Table A3***Perceived Support of Action Regulation Scale in English*

Items	Usability	Information processing
... can perceive all relevant information accurately.	1	Acq
... can determine precisely whether I am acting in the best possible way with regard to my goal.	1	Ana
... can accurately derive possible action options and their effects.	1	Ana
... can decide optimally how to adapt my actions with regard to my goal.	1	Dec
... can implement my actions in the best possible way with regard to my goal.	1	Imp
... can perceive all relevant information effortlessly.	2	Acq
... can determine without effort whether I am acting in the best possible way with regard to my goal.	2	Ana
... can effortlessly derive possible action options and their effects.	2	Ana
... can decide quickly how to adapt my actions with regard to my goal.	2	Dec
... can implement my actions effortlessly with regard to my goal.	2	Imp
... am sure that I have included all relevant information to improve my behaviour.	3	Acq
... feel confident in determining whether I am acting in the best possible way with regard to my goal.	3	Ana
... feel confident in deriving possible action options and their effects.	3	Ana
... can confidently decide how to adapt my actions with regard to my goal.	3	Dec
... feel confident in implementing my actions in the best possible way with regard to my goal.	3	Imp

*Note.* 1 = effectiveness, 2 = efficiency, 3 = confidence, Acq = information acquisition, Ana = information analysis, Dec = decision selection, Imp = action implementation. Instruction text: "While you are trying to drive as energy-efficiently as possible (= goal), various cognitive processes can play a role, such as: paying attention to relevant information from the vehicle or the environment; checking, recognising and understanding how action deviates from the goal; deriving possible options of action and weighing up their advantages and disadvantages; deciding on the optimal course of action and implementing it. Firstly, it is about how [well or accurately / effortlessly / confidently] you were able to achieve the goal of driving energy-efficiently using the information available. By 'available information' we mean [...]. Please indicate your level of agreement with the following statements. With the help of the information available, I..."

**Table A4**

*Support of the Mental Model within Action Regulation Scale in English*

No	Item text
1	... help me understand which aspects I need to consider to drive as energy-efficiently as possible.
2	... help me to understand how to drive in an energy-efficient way.
3	... help me understand why driving is energy-efficient in a certain way.
4	... allow me to improve my existing knowledge of energy-efficient driving.
5	... provide me with a complete knowledge of energy-efficient driving behaviour.

*Note.* Instruction text: “What role does the available information play in your understanding of how to drive as energy-efficiently as possible? By ‘available information’ we mean all information that relates to your goal (ecodriving), [especially the tips received and also] information from the vehicle and the environment. Please indicate your level of agreement with the following statements. The information available...”

**Table A5**

*Perceived Support of the Mental Model within Action Regulation Scale in German*

No	Item text
1	... helfen mir dabei zu verstehen, welche Aspekte ich berücksichtigen muss, um so energieeffizient wie möglich zu fahren.
2	... unterstützen mich dabei zu verstehen, wie man energieeffizient fährt.
3	... helfen mir dabei zu verstehen, warum es energieeffizient ist, auf eine bestimmte Art und Weise zu fahren.
4	... erlauben es mir, mein bestehendes Wissen über energieeffizientes Fahren zu verbessern.
5	... vermitteln mir ein vollständiges Wissen über energieeffizientes Fahrverhalten.

*Note.* Instruction text: „Welche Rolle spielen die verfügbaren Informationen bei Ihrem Verständnis darüber, möglichst energieeffizient zu fahren? Mit ‘verfügbaren Informationen’ meinen wir alle Informationen, die sich auf Ihr Ziel (energieeffizientes Fahren) beziehen, also [vor allem die erhaltenen Tipps und auch die] Informationen aus Fahrzeug und Umwelt. Bitte geben Sie den Grad Ihrer Zustimmung zu folgenden Aussagen an. Die verfügbaren Informationen...”

## Appendix B: Descriptive and Statistical Results

Table B1

*Descriptive and Inferential Statistics of the Z-Standardised Driving Metrics*

Metric	Control	Generic	Know-how-and-why	Test statistic F(1,44)	p	r
	M (SD)	M (SD)	M (SD)			
Energy consumption (mean)	0.31 (0.67)	-0.10 (0.40)	-0.17 (0.45)	7.34 <sup>b</sup>	.010*	.38
Throttle position (mean)	0.23 (0.42)	-0.06 (0.39)	-0.16 (0.41)	7.47 <sup>b</sup>	.009**	.38
Throttle position (median)	-0.01 (0.32)	0.02 (0.35)	-0.01 (0.26)	<0.01 <sup>b</sup>	.977	-.01
Throttle position (SD)	0.38 (0.56)	-0.09 (0.48)	-0.25 (0.54)	11.69 <sup>b</sup>	.001**	.46
Braking pedal pressure (mean)	0.12 (0.51)	-0.07 (0.42)	-0.03 (0.62)	0.98 <sup>b</sup>	.329	.15
Braking pedal pressure (median)	0.09 (0.42)	-0.07 (0.37)	-0.02 (0.49)	0.89 <sup>b</sup>	.351	.14
Braking pedal pressure (SD)	0.14 (0.60)	-0.06 (0.41)	-0.03 (0.75)	0.91 <sup>b</sup>	.345	.14
Velocity (mean)	0.15 (0.42)	0.01 (0.45)	-0.14 (0.31)	3.55 <sup>b</sup>	.066	.27
Velocity (median)	0.14 (0.37)	0.02 (0.52)	-0.16 (0.35)	3.31 <sup>b</sup>	.076	.26
Velocity (SD)	0.16 (0.31)	-0.05 (0.37)	-0.11 (0.32)	5.48 <sup>b</sup>	.024*	.33

Note.  $n'_{control} = 15$ ,  $n'_{generic} = 16$ ,  $n'_{know-how-and-why} = 16$ .

\*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ .

Table B2

*Descriptive and Inferential Statistics of the Subjective Scales*

Scale	Control	Generic	Know-how-and-why	Test statistic F(1, 47)	p	r
	M (SD)	M (SD)	M (SD)			
<i>Perceived support of action regulation</i>						
Effectiveness	4.10 (1.01)	4.39 (0.91)	4.96 (0.71)	6.02	.018*	.34
Efficiency	3.99 (1.24)	4.54 (1.01)	4.69 (0.80)	4.20	.046*	.29
Confidence	3.84 (1.15)	4.51 (1.00)	4.58 (0.87)	5.37	.025*	.32
Information acquisition	3.96 (1.03)	4.48 (1.07)	4.83 (0.64)	6.99	.011*	.37
Information analysis	3.94 (1.15)	4.35 (0.99)	4.74 (0.72)	5.16	.028*	.32
Decision selection	4.04 (1.19)	4.52 (0.92)	4.65 (0.88)	3.33	.074	.26
Action implementation	4.00 (1.24)	4.69 (0.86)	4.74 (0.81)	5.65	.022*	.33
<i>Perceived support of the mental model</i>	3.30 (1.07)	4.19 (1.21)	5.04 (0.68)	21.98	< .001***	.56
<i>Uncertainty due to a lack of knowledge</i>	2.89 (1.26)	2.46 (1.05)	2.34 (1.01)	2.26	.139	.22
<i>Gain in ecodriving knowledge</i>	0.44 (0.72)	1.40 (1.05)	1.50 (1.33)	9.95	.003**	.41

Note.  $n_{control} = 16$ ,  $n_{generic} = 16$ ,  $n_{know-how-and-why} = 18$ .

\*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ .

## 8. Study 4: Explaining Ecodriving Recommendations: The Effect of Auditory Tip-Based Feedback on Ecodriving Performance and Perceived Action Regulation Support

### 8.1. Abstract

Ecodriving feedback systems differ in how much they automate cognitive processes, ranging from pure consumption displays to direct action recommendations. Increased automation may reduce drivers' engagement with underlying system dynamics, limiting learning opportunities and impairing mental model development, both essential for flexible and adaptive action regulation. Integrating explanatory auditory feedback that conveys not only know-how but also the rationale behind strategies (know-why) could close this gap, resembling support by knowledgeable co-drivers. This study investigates how different levels of cognitive scaffolding in ecodriving feedback affect action regulation, mental model support, knowledge, driving activity workload, and information processing awareness.

In a driving simulator experiment ( $N = 112$ ), participants were randomly assigned to one of three conditions: (G1) conventional consumption display, (G2) additional optimal speed recommendations, (G3) additional auditory explanatory feedback. Contrast analyses revealed significant linear trends, with G3 showing the best performance in pedal interaction patterns and energy consumption. Moreover, perceived mental model support was significantly higher in G3 than in G1. All groups showed significant gains in perceived ecodriving knowledge. However, G3 also led to lower ratings of information acquisition support and information processing awareness compared to G1, and to the highest driving activity workload. These findings highlight the potential of explanatory, multi-modal feedback to advance support systems by fostering mental model development and driving performance. Future research should explore how to balance informativeness and cognitive load through context-sensitive, adaptive feedback delivery, and examine whether the benefits consolidate over time and in real-world contexts.

**Keywords:** Energy efficiency, ecodriving feedback, knowledge, human-automation interaction, action regulation

### 8.2. Introduction

Effective operational ecodriving, i.e., the execution of driving manoeuvres (Sivak & Schoettle, 2012; Wang et al., 2020), requires adaptive action control, where drivers continuously monitor and integrate system and environmental variables such as speed, pedal position, energy consumption, and traffic. They must derive the impact of driving strategies on energy efficiency and regulate their actions accordingly, similar to other facets of driving behaviour (Fuller, 2005; Summala, 2007). To successfully engage in ecodriving, drivers must construct a *situational model* (i.e., situation awareness; Baumann & Krems, 2007; Endsley, 2000) based on knowledge (i.e., mental model; Carroll & Olson, 1987) that enables efficient decision-making based on understanding system-environment interrelations. Consequently, well-designed ecodriving feedback should foster correct and adequate *mental models* of how to drive energy-efficiently and why these driving strategies are most energy-efficient (Carroll & Olson, 1987; Sureth et al., 2019). A well-structured *mental model* supports understanding, allows

accurate predictions, and enables drivers to explore alternative actions (Carroll & Olson, 1988; Johnson-Laird, 1994, 2010; Nowak et al., 2013; Rouse & Morris, 1986). This is especially relevant in energy-efficient driving of battery-electric vehicles (BEVs), where unfamiliar energy metrics or indicators are less intuitively linked to driving behaviour and understanding (Moll, Heidinger, et al., 2025; Neumann & Krems, 2016; Strömberg et al., 2011).

To regulate their ecodriving behaviour effectively, drivers require declarative knowledge about action alternatives in specific situations (e.g., braking strategies such as mechanical braking, regenerative braking, or neutral gliding) and effectiveness knowledge (Frick et al., 2004; Liefländer et al., 2015), which influences the perceived value of action alternatives and thus determines whether they are implemented (e.g., braking via neutral gliding is most energy-efficient). Procedural knowledge allows drivers to quickly identify, select, and apply strategies based on situational demands (see also the approach of activating acquired rules or procedures at the rule-based level in human performance models; Rasmussen, 1983). Those links between situational demands and action (e.g., “If you accelerate from a standstill, then press the driving pedal rather moderately.”) represent a key basis for regulating ecodriving behaviour because they directly explicate the relationships, are required for output prediction and enable flexibility and transfer to perceptually or structurally different situations by creating representations of structural properties of driving strategies (for a detailed review in the context of controlling complex dynamic environments see Osman, 2010).

However, a key challenge in ecodriving is that different ecodriving feedback approaches, that is, ways of coupling human action regulation with system information, differ in the extent to which they automate cognitive processes involved in action regulation (see types and levels of human interaction with automation; Parasuraman et al., 2000). While standard approaches focusing on raw values of effect on the environment (e.g., consumption displays) require drivers to effortfully infer energy-efficient strategies independently, others simplify information analysis and decision-making by directly suggesting optimal actions, yet without fostering a deeper understanding of energy dynamics. This raises the question of how different ecodriving feedback approaches influence not just performance but also the formation of accurate mental representations of ecodriving.

### **Role of Knowledge within Different Ecodriving Feedback Approaches**

In general, there are different types of couplings between human action regulation and vehicle systems, each of which entails distinct demands on understanding processes, cognitive engagement, and proximity to action. These couplings shape the way drivers mentally

represent ecodriving during the driving task. In general, two primary ecodriving support approaches can be distinguished:

1. Feedback approaches that vary in the degrees of automation, from a) rather low-level automated feedback that merely presents raw energy-relevant data (e.g., real-time energy consumption or power), to b) more advanced recommender systems offering action recommendations (e.g., optimal speed or pedal position) based on intelligent algorithms like dynamic programming (DP) and Model Predictive Control (MPC; see Method section).
2. Training or learning approaches that provide explicit behavioural strategies tailored to situational demands, often including technical explanations to promote deeper comprehension of underlying energy dynamics, and varying between rather static (e.g., brochures, tip lists) to dynamic approaches (e.g., applied training course, behaviour-dependent advice during driving).

These different approaches can not merely differ in content or form but also in their degree of automation in information processing. Thus, the extent to which the interface rather than the driver performs information acquisition and analysis can shape how drivers internalise and adapt energy-efficient behaviour while driving.

Monitoring energy consumption feedback (1a) is widely discussed to support learning about energy-efficient driving strategies (Dahlinger et al., 2018; Franke et al., 2017; Stillwater & Kurani, 2013). Although drivers often prefer instantaneous consumption displays (Loumidi et al., 2011), studies indicate that they do not necessarily improve energy efficiency (Martin et al., 2013). Regarding judgments of trips' energy efficiency, there seems to be no significant scope for improvement with different forms of consumption feedback (i.e., consumption bar, consumption trace, or energy flow display; Gödker et al., 2024). Additionally, previous work has shown that conventional instant consumption feedback leads to systematic biases in energy efficiency perception, consistent with static biases in speed perception, braking capacity, travel time, and fuel consumption (Moll & Franke, 2021; Svenson, 2021). Overall, exploiting the efficiency potential with currently available energy efficiency information seems difficult, and drivers develop inefficient ecodriving strategies (Arend et al., 2019; Franke et al., 2016).

Action-related ecodriving recommendations (1b) provide concrete suggestions for speed, gear selection, or pedal positions (i.e., target value) by analysing vehicle efficiency characteristics and environmental data in real-time, such as road slope, traffic regulations, or signal timing. Compared to typical consumption displays, these systems represent a higher automated degree of information acquisition, information analysis, and decision selection (see Parasuraman et al., 2000; Ruscio et al., 2024). Their key advantage lies in their proximity to action implementation:

they may simplify decision-making by offering ready-to-implement strategies that reduce cognitive load and provide both the current and target state necessary for action regulation. However, designing feedback approaches that regulate driver behaviour through higher automated information processing involves a fundamental trade-off. While automation can enhance efficient and confident action regulation by reducing cognitive load and narrowing attention to a clearly defined target state, it may simultaneously undermine drivers' ability to develop adequate *mental models* of energy-efficient driving. Potentially low-engagement feedback may reduce the need for deliberate reasoning, which in turn may hinder awareness of knowledge gaps and the development of robust situational understanding, particularly when perceived knowledge is misaligned with actual knowledge.

At the same time, higher automated systems might conflict with drivers' existing *mental models* or be perceived as opaque, especially when feedback originates from complex or non-transparent ("black-box") artificial intelligence (AI). In such cases, drivers may distrust the system, misinterpret recommendations, or expend additional cognitive effort trying to make sense of the guidance, potentially leading to inefficient or unconfident behaviour control. This mismatch between system output and drivers' understanding could increase uncertainty and diminish perceived self-efficacy, particularly when drivers are confronted with a target state (i.e., task demand) that feels further removed from their perceived capabilities (cf. *Task-Capability Interface model*, Fuller, 2005, 2011). Empirical findings support this tension: users with limited domain knowledge are likely to follow advice from AI systems without critical reflection, reducing their awareness of knowledge gaps (Gomez et al., 2023). Opacity in AI systems can amplify this effect, leading to anchoring biases, reduced engagement, and overreliance on AI outputs (Lebovitz et al., 2022).

Thus, while higher automated driving-related feedback can potentially reduce energy consumption (e.g., Allison et al., 2019), it also bears the risk of diminishing cognitive engagement, trust calibration, and self-reflection—especially when not paired with mechanisms that support user understanding and transparency. This highlights the importance of well-founded calibration of automated guidance with drivers' autonomy and *mental model* development.

A stronger comprehension-based coupling of human action regulation with the vehicle system based on explanatory feedback seems promising. The need for understandable and transparent system decisions has been widely discussed in the broader research field of explainable artificial intelligence (XAI; Arrieta et al., 2019; Gomez et al., 2023; Miller, 2019, 2023; Tiddi & Schlobach, 2022; Vilone & Longo, 2021). Research shows that explanations of causal relationships between inputs and the model's predictions can improve decision effectiveness, trust, and the ability to transfer knowledge across contexts. If there is a lack of explainability,

the awareness of one's knowledge gaps often remains low (Lebovitz et al., 2022; Tiddi & Schlobach, 2022). In the context of ecodriving, explanatory feedback could play a similar role, clarifying the know-how and know-why behind sensorimotor recommendations and enhancing drivers' ability to make independent, well-informed decisions. However, while the potential benefits of explanatory feedback have been widely recognised, the specific mechanisms through which such feedback can best support ecodriving behaviour remain underexplored. Initial studies have started to examine such feedback approaches independent of higher-level automated recommendation systems, particularly in the form of rules or tips. These approaches represent concrete examples of explanatory feedback aimed at fostering deeper understanding during driving.

### **Current Research on Comprehension-Based Ecodriving Feedback**

Current research suggests that ecodriving feedback could improve fuel efficiency when drivers understand the rationale behind driving strategies (Arend et al., 2019). Furthermore, psychological grounded formulations specifying when, where, and how behaviour leads to goal achievement (implementation intentions; Gollwitzer, 1993, 1999, 2014; Gollwitzer et al., 2010; Gollwitzer & Sheeran, 2006; Sheeran et al., 2025) have shown to reduce consumption by 4%–11.3% in field studies when supported by technical explanations (Moll, Banach, et al., 2025; Sureth et al., 2019). Yet, little research has examined how these principles apply to real-time, manoeuvre-specific, and verbal ecodriving feedback (see *Table A1* in Appendix A for a literature overview and formulation examples).

First studies show that presenting ecodriving tips before driving, simple advice, or explanations of how, when, and why to implement simple, generic rules can enhance driving behaviour and reduce emissions (Azzi et al., 2011; Beloufa et al., 2019; Günther et al., 2019; van der Voort et al., 2001). Besides, feedback related to actual driving performance is more effective than generic information from static sources (Tu et al., 2022; Zhao et al., 2015). Combined theoretical and practical training leads to greater improvement than theoretical learning alone (Andrieu & Saint Pierre, 2012; Symmons et al., 2008). Active application of ecodriving rules helps drivers understand principles and improve behaviour (Wu et al., 2017), aligning with broader educational research on effective skill development (Freeman et al., 2014; McCarthy & Anderson, 2000; Prince, 2004).

Past studies exhibit several limitations: a) static rather than dynamic tips were used, b) manoeuvre- and situation-specific formulations were not considered, c) tips were not combined with real-time recommendation systems, d) primarily visual feedback was examined, and e) the focus lay on combustion vehicles.

Most studies have relied on a) static, generic tips rather than dynamically adapting to real-time driving conditions and specific manoeuvres. Compared to purely sensorimotor recommendations of optimal speed, additional explanatory feedback in the form of tips could explicitly specify how an action should be executed (*know-how*) and why it is effective (*know-why*), thereby promoting more flexible, transferable learning and active decision-making. Previous research has not adequately addressed b) concrete manoeuvre- and situation-specific guidance for various conditions like traffic light phases, stop-and-go traffic, or road gradients (e.g., specific pedal position while accelerating, or concrete speed to drive through green traffic light phases). Existing tips often fail to address how specific actions, such as accelerating from a standstill or neutral gliding in response to downhill gradients, should be adapted to particular situational demands. However, ecodriving performance crucially depends on whether the feedback enables precise behavioural tuning at the manoeuvre level.

Previously studied, rule-based feedback has also been implemented c) independently of recommendation systems. Decision support and artificial intelligence research suggest that explaining recommended actions can improve decision quality and trust (Miller, 2019, 2023; Singh et al., 2023). However, these findings have not been applied in ecodriving contexts, where recommendations must be interpreted and executed within seconds. While prior research has investigated predictive road information (e.g., "rolling ahead of curve") as a form of explanatory feedback (Daun et al., 2013), it remains unclear how explanations formulated more precisely regarding action implementation affect ecodriving.

Furthermore, most studies relied on d) visual presentation, despite findings that visual displays increase cognitive load and potential distraction risks (Kircher et al., 2014; Rouzikhah et al., 2013). Research shows that compared to visual-only feedback, adding auditory elements (i.e., simple sound signals for undesirable events, visual displays with additional voice prompts or alerts) leads to better energy-efficiency, lower speeds, better pedal positions, and decreased visual distraction (Adell et al., 2008; Hammerschmidt & Hermann, 2017; Hibberd et al., 2015; Jamson et al., 2015; Rolim et al., 2014; Zhao et al., 2015). Thus, distributing information across multiple modalities can improve cognitive efficiency. However, the interaction between visual recommendations and additional auditory explanatory feedback needs further exploration. In connection with modality, timing is also crucial for effectiveness as immediate feedback leads to better learning retention than delayed feedback (Dihoff et al., 2004; Dijksterhuis et al., 2015; Kulik & Kulik, 1988; Van Der Kleij et al., 2015) and positively influences ecodriving behaviours (Zhao et al., 2015). Auditory presentation offers the advantage of delivering cognitively demanding information precisely and as close to the relevant behaviour as possible while reducing visual distraction.

Regarding the motor type, the e) focus was primarily on internal combustion vehicles (ICEVs), with few exceptions (Günther et al., 2019; Moll, Banach, et al., 2025; Sureth et al., 2019), even if previous research has not always explicitly specified the powertrain to which the tips referred. Although some generic strategies apply to all motor types (e.g., avoiding unnecessary accelerations), there are several strategic differences and new strategies that must be applied to BEVs, like preferring gliding neutrally instead of regenerative braking. Furthermore, the vehicle-specific energy model and its consequences for pedal interaction over time have to be considered for the highest possible specification of the required action implementation (e.g., concrete pedal position for optimal moving through the vehicle's conversion efficiency map while accelerating).

### 8.3. Present Research

Building on the identified research gaps, the present study addresses the need for a deeper understanding of how drivers cognitively and behaviourally respond to different ecodriving feedback approaches, especially when balancing automated guidance with *mental model* formation. To this end, the study extends prior research on compact tip lists and rule-based feedback formats aimed at helping drivers understand the link between situational demands and appropriate driving actions (Moll, Banach, et al., 2025; e.g., Sureth et al., 2019; Zhao et al., 2015). It also integrates recent advancements in intelligent recommendation algorithms and works on the role of explanatory information in human-AI interaction (Miller, 2019, 2023). The goal is to evaluate how combined visual speed recommendations with auditory know-how-and-why tips affect driving performance, subjective ecodriving knowledge, perceived support of *mental model* and action regulation, subjective information processing awareness as a measure focusing on the explanatory quality of recommendations (i.e., in the sense of common XAI approaches), and experienced driving activity workload. Specifically, three feedback conditions are compared: (1) a conventional consumption display (*control*), (2) an additional visual recommendation display (*recommendation*), and (3) additional auditory explanatory feedback (*explanatory*).

The auditory verbal tips are designed to clarify how and why specific driving actions improve energy efficiency, translating complex input-output relationships into cognitively digestible, actionable rules. However, this process involves a fundamental trade-off: while simplification may facilitate understanding and transfer, it also risks losing precision and nuance. A central challenge in implementing explanatory feedback in the form of rule-based tips is the linguistic condensation of energy efficiency dynamics into an understandable and conveyable representation of input-output relationships (i.e., close to interpersonal communication). This transformation inherently involves a conflict between retaining quantitative precision and

facilitating cognitive processing and transfer. The extent to which drivers can effectively integrate these rules into their *mental models*, increase effectiveness, efficiency and confidence within action regulation, and apply the knowledge to improve driving performance remains an open question.

Understanding verbal tips as a naturalistic co-driver-like support system, this study examines how explanatory feedback enhances drivers' cognitive engagement and driving performance, especially in a fast-paced context where decisions must be made with limited attentional resources. Prior research on decision support suggests that concrete, actionable formulations are more effective than generic explanations, particularly in unfamiliar contexts or high-demand situations (Singh et al., 2023). Yet, in the ecodriving domain, the degree to which such feedback fosters successful action regulation and refined *mental models* has to be systematically explored.

While prior research and theoretical frameworks suggest that higher transparency and explanatory feedback may better support *mental model* formation, the effects of different feedback approaches on subjective measures cannot be fully explained by isolated characteristics (e.g., presence of explanation or degree of automation). Instead, their impact results from a complex interplay between cognitive engagement, system transparency, driver autonomy, and existing *mental models* (i.e., cognitive scaffolding). This coupling varies depending on situational context and task demands, and may even lead to increased workload when system knowledge must be integrated into decision-making, even under higher automation. Given this complexity and the limited theoretical precision regarding the direction and strength of effects, we predominantly refrain from formulating directional hypotheses. Thus, the following research questions are examined:

- RQ1** Is there a difference in perceived support of the *mental model* within action regulation between the *explanatory*, *recommendation*, and *control* conditions?
- RQ2** Is there a difference in subjective (verbalisable) ecodriving knowledge between the *explanatory*, *recommendation*, and *control* conditions?
- RQ3** Is there a difference in perceived support of action regulation between the *explanatory*, *recommendation*, and *control* conditions?

In contexts where system recommendations affect real-time action regulation, subjective information processing awareness (SIPA; Schrills et al., 2024; Schrills & Franke, 2023) plays a central role in mediating trust, engagement, and perceived control. Especially under conditions of partial automation, where drivers must integrate external feedback into their reasoning, SIPA reflects the user's ability to monitor, comprehend, and predict system behaviour. Providing auditory, rule-based explanatory feedback may enhance SIPA, making the rationale behind

speed and pedal suggestions more transparent. At the same time, potential misalignments between recommendations and explanatory feedback may occur. For instance, while the verbal tips are intended to explain energy-efficient strategies, they often refer to pedal actions (know-how), whereas the visual display communicates speed targets. As the auditory tips precede the visual speed recommendation, and thus a fully inferable connection may not be given, drivers may perceive inconsistencies between what is said and what is shown. Such incoherence can impede the construction of a coherent *mental model*, thereby reducing SIPA, especially in the driving context where multimodal cues must be integrated rapidly. Thus, while explanatory feedback may enhance transparency, its effectiveness depends on the perceived coherence between different system elements and the user's ability to relate them to ongoing driving behaviour.

**RQ4** Is there a difference in SIPA scores between the *explanatory*, *recommendation*, and *control* conditions?

While explanatory feedback can foster deeper understanding, it imposes greater attentional demands. Interpreting and mentally simulating rule-based tips requires active cognitive engagement and may interfere with concurrent driving tasks. As a result, an increase in perceived driving activity workload can be expected, since users must allocate attention not only to the environment and vehicle control, but also to the integration of verbal guidance and visual recommendations. Given that the feedback conditions differ in both the amount and complexity of information provided, it is plausible that driving workload will be differentially affected. Specifically, more complex feedback formats may increase the cognitive demands required for information integration and concurrent task management.

**H1** Driving activity workload will be highest in the *explanatory* condition and lowest in the *control* condition.

Building on prior research demonstrating beneficial effects of *know-how-and-why* feedback (Moll, Banach, et al., 2025; Sureth et al., 2019) and speed recommendations (Allison et al., 2019) on consumption, we hypothesise that explanatory information enhances ecodriving performance beyond the effect of a recommended optimal speed alone.

**H2** The ecodriving performance will be highest in the *explanatory* condition and lowest in the *control* condition.

## 8.4. Method

### Participants

A total of 132 participants were recruited via student e-mail distribution lists, university forums (University of Lübeck, Technische Hochschule Lübeck), and through posters displayed in a student dormitory and the university cafeteria. They had to be at least 18 years old, possess a driving license, and be fluent in German to be included in the experiment. All participants were compensated €21.00 for their participation time or course credit for psychology and media informatics students. Ethics approval was granted by the Ethics Committee of the University of Lübeck before the experiment's start (file number 2024-180).

Four participants aborted the experiment due to simulator sickness, and 15 had to be excluded due to irregular procedures (e.g., display or general technical failures). The resulting sample included 112 participants ( $N = 112$ ) between 18 and 57 years old ( $M = 24.1$ ,  $SD = 5.5$ ). Among them, 59 participants (53%) were female, and 25 (22%) had a university degree. The total driving experience across all vehicles was  $M = 42461.4$  km ( $SD = 72207.9$ ). In total, 32 participants (29% of the sample) had driven at least 50 km in a BEV. The total driving experience of these participants with BEVs was  $M = 1279.9$  km ( $SD = 1931.6$  km). A further 21 participants (19%) reported experience with (plug-in) hybrid electric vehicles (HEVs/PHEVs). Regarding the Affinity for Technology Interaction (ATI; Franke et al., 2019), the sample showed a wide range (ranging from 1.6 to 6.0), with a mean score of 4.0 ( $SD = 1.0$ ), higher than values reported for the general population ( $M = 3.6$ ,  $SD = 1.1$ ; see Franke et al., 2019).

Of the final sample, 3 participants had corrupted driving data sets due to temporary technical problems in the data logging. Therefore, we excluded these datasets from all analyses that used driving simulator data, resulting in a reduced sample  $N' = 109$ .

### BEV Driving Simulator

The study was conducted in the EcoSimLab (Gödker et al., 2024) driving simulator at the Institute of Multimedia and Interactive Systems, University of Lübeck. The simulator featured a virtual driving environment based on the EcoDrivingTestPark and used a simulated Renault Zoe electric vehicle. The hardware setup included three 55" monitors operating at 120 Hz to provide a 180° field of view, as well as a Fanatec simulation rig consisting of a seat, wheelbase, and pedals. A compact steering wheel modelled after the Renault Zoe was mounted to enhance realism; both the wheel and the pedals included force feedback functionality. BeamNG.tech, an extended research variant of the BeamNG.drive simulation platform, was used as the simulation

software (BeamNG GmbH, 2022). All further details on the driving simulation can be found in Gödker et al. (2024).

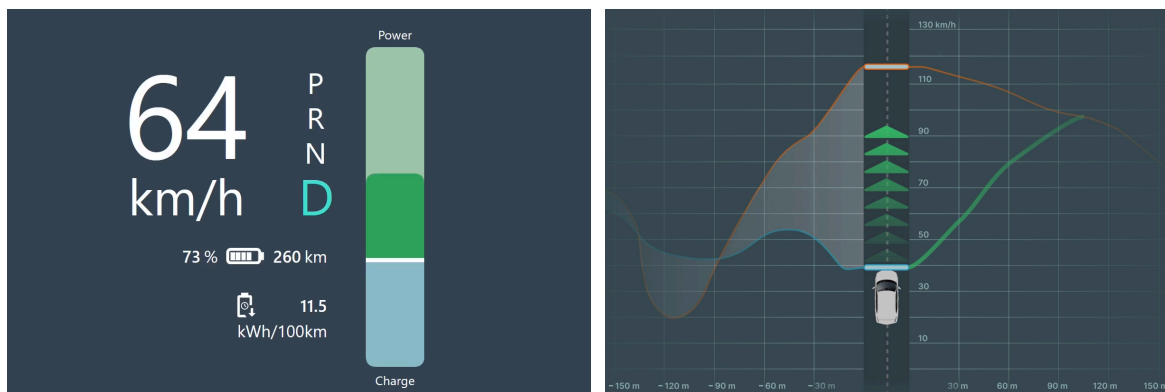
### Ecodriving Displays

The **conventional consumption display** (see Figure 1) was designed to reflect common energy display elements in current BEVs (i.e., as a status quo). To ensure ecological validity, the ten most registered BEV models in Europe in 2023 were identified: Tesla Model Y, Tesla Model 3, Volkswagen ID.3, Volkswagen ID.4, MG4, Skoda Enyaq, Fiat/Abarth 500e, Dacia Spring, Volvo C40, BMW i4 (JATO, 2024). Manuals of these vehicles were systematically reviewed to analyse the design and content of their in-vehicle energy displays.

The analysis focused on six key dimensions: (1) the type of consumption information (instantaneous vs. average consumption), (2) the display format (e.g., bar, trace, categorical or symbolic codings), (3) the orientation of the display (e.g., vertical, horizontal, or radial bars), (4) the presence of state-of-charge (SOC) and remaining range information, (5) the inclusion of driving mode indicators, and (6) the presence of predictive elements or explicit action guidance.

**Figure 1**

*Status Quo Consumption Display (left) and Recommendation Display Suggesting Optimal Speeds (right)*



The most frequently observed features across these vehicles were: instantaneous power and recovered energy, bar-type visualisations (typically vertical or radial-vertical), indicators for SOC and remaining range, and current speed. These commonly shared characteristics were integrated into a representative conventional consumption display for use in the study, which was presented on a 13.5” screen positioned behind the steering wheel, corresponding to the typical location of an in-vehicle dashboard display. When the bar was deflected into the upper

(positive) range and coloured green, electrical power was drawn from the battery. When it moved into the lower (negative) range and was coloured blue, power was returned to the battery via regenerative braking. The magnitude of the bar's deflection, whether upward or downward, indicated the level of power consumption or recovery. If no deflection was visible, no power was being consumed or recuperated.

The **recommendation display** (see Figure 1) was designed as a continuous recommender system based on an intelligent optimisation-based system architecture, EcoMPC, which integrates both precomputed and adaptive optimisation to generate energy-efficient driving guidance over several segments of the route. The system combined DP and MPC to ensure both global optimality and real-time adaptability. The DP module precomputed a globally optimal speed profile (orange curve) by considering road curvature, speed limits, stop signs, road gradients, and a detailed vehicle model of the Renault Zoe Q90 (Gödker et al., 2024; Heidinger et al., 2023). This approach ensured that each local speed decision was embedded within a globally energy-minimising trajectory. DP ensured optimal balance between energy consumption, travel time, and comfort (Lin et al., 2014; Sciarretta et al., 2015). The resulting reference trajectory was computed offline across segmented routes, considering constraints such as speed limits and vehicle capabilities. To enable adaptive real-time guidance, the MPC module continuously adjusted the speed recommendation based on current driving conditions to track the DP reference while accounting for real-time disturbances.

The resulting optimisation output was visually represented on a 10.5" Samsung Galaxy S4 tablet, which was mounted below the simulation monitors to the right of the steering wheel. The orange curve displayed the DP reference trajectory, illustrating the globally optimal speed profile. The green curve represented the MPC-based adaptive recommendation, updating in real time. The display continuously compared the driver's actual speed with the optimal speed within a 150-meter window, spanning both past and upcoming road segments, and provided immediate visual feedback on deviations. Green arrows indicated the optimal speed at a 50-meter preview distance to further support anticipatory driving, encouraging proactive energy-efficient behaviour.

### **Auditory Explanatory Feedback**

The goal of the auditory feedback condition was to explain the intelligent EcoMPC algorithm through concise verbal feedback that makes the system's reasoning transparent to the driver, focusing on action-integrated explanations of manoeuvres. This approach aimed to help drivers understand why specific speed choices were recommended and how they should be implemented, thereby fostering both comprehension and compliance. Setting the stage, we

sought to derive rule-based tips that could serve as standardised, reproducible explanations for typical ecodriving situations while staying consistent with the optimisation logic of the EcoMPC algorithm. To extract the *know-how and know-why* of the explanatory feedback, we used a multi-step procedure combining prototypical driving manoeuvres, efficiency analysis, and expert validation. In an ideal world, one could directly generate explanations in real time from the EcoMPC algorithm itself, based on current driving behaviour. However, for standardisation and replicability—ensuring identical feedback timing, frequency, and formulations across participants—we opted for an approximation approach.

First, a set of representative driving manoeuvres was identified based on their relevance for energy efficiency and presence in the main driving sectors of the EcoDrivingTestPark (see Procedure section). These included: (1) acceleration on flat roads at lower or at higher speeds, (2) braking on flat, uphill, or downhill segments, (3) strategic speed selection at higher speeds, (4) anticipation of stop-and-go traffic, and (5) anticipation of traffic light phases.

In a second stage, these representative driving manoeuvres were first simulated using DP to determine the control strategies the algorithm would recommend under different driving conditions. To translate the resulting speed and torque profiles into corresponding, verbalisable pedal dynamics, systematic testing was conducted by two BEV experts in the driving simulator as a calibration and validation step. Experts received real-time feedback through a visual representation of the motor's conversion efficiency map and pedal positions. This setup enabled the reproduction and fine-tuning of manoeuvre-specific pedal position curves that align with algorithm-derived trajectories and optimal paths indicated by the conversion efficiency map.

In the third stage, insights were integrated to formulate know-how-and-why tips that convey the algorithm's logic in an actionable, rule-based format. Tip formulations were refined across several iterations, starting from detailed explanations grounded in prior psychologically informed approaches (e.g., Moll, Banach, et al., 2025; Sureth et al., 2019). The tips were shortened for real-time feasibility and validated through iterative feedback from five engineering and engineering psychology experts with 10 years of professional experience on average (see Table 1 for the final tip set).

## Study 4: Explaining Ecodriving Recommendations

**Table 1**

*Explanatory Feedback for the Various Driving Situations During the Experiment*

Manoeuvre	Know-how	Know-why
Accelerating at lower speeds (< 60 km/h)	Accelerate below 60 km/h with a steady pedal position of approximately 30%.	This allows you to move through the motor's efficiency ranges optimally.
Accelerating at higher speeds (> 60 km/h)	Accelerate above 60 km/h with a steady pedal position of approximately 40%.	This allows you to move through the motor's efficiency ranges optimally.
Braking	When braking, try to coast by gently pressing the accelerator at around 1%. If that's not enough, release the pedals to activate mild recuperation. If mild recuperation is still insufficient, press the brake pedal—but not too hard.  <i>Uphill:</i> When braking uphill, rely more on gliding depending on the slope, and recuperate less. To do so, press the accelerator gently at 1%. To recuperate, release the pedals. Press the brake pedal lightly to come to a stop.  <i>Downhill:</i> Start braking before the descent by gently pressing the accelerator at 1%. Then, release the pedals to recuperate. Press the brake pedal—gently—to apply stronger recuperation depending on the slope.	This way, momentum is used effectively and partially recovered instead of being completely lost through strong braking.  This way, momentum is used efficiently, conversion losses are reduced, and part of the momentum is recovered instead of completely lost through braking.
Speed selection at higher speeds	Press the accelerator in accordance with the recommended, preferably low and steady speed.	At high speeds, energy consumption increases disproportionately due to air resistance.
Anticipation of Stop-and-Go	Drive at the recommended low speed in stop-and-go traffic to stay in motion as evenly as possible.	This way, you avoid building up unnecessary momentum and wasting it through braking.
Anticipation of traffic light phases	<i>While braking:</i> Adjust your speed to the recommended value based on the traffic light phase to stay in motion smoothly. Recuperate when going downhill by releasing the pedals and, if needed, by gently pressing the brake pedal.  <i>While Accelerating:</i> Accelerate below 60 km/h with a steady pedal position of approximately 30% to reach the recommended speed.	This way, you can pass the traffic light while it's green, avoid building up unnecessary momentum, and partially recover energy instead of wasting it through braking.  This helps you drive through the motor's efficiency ranges as effectively as possible and pass the green lights smoothly, without building up excess momentum and wasting it through braking.

*Note.* The tips are valid for the given energy model (Zoe Q90) and driving situations.

Concerning speed selection and the anticipation of traffic and traffic light phases, the formulations refer to the speed suggested by the recommendation display. This ensures that the rule-based tips are aligned with the underlying optimisation strategy, maintaining consistency between the visual and auditory feedback. This avoids conflicting cues and supports coherent

decision-making aimed at maximising energy efficiency. The tips related to acceleration and braking manoeuvres emphasise the concrete pedal interaction requirements needed to implement the recommended speed. This helps translate abstract target values into actionable control strategies, guiding participants toward timely and efficient execution in line with the optimal speed trajectory.

The finalised tips were converted into audio files using the AI-based tool *Speechify* (Speechify Inc., 2025) to ensure natural prosody and appropriate timing for auditory presentation during driving. They were positioned along the routes based on their action relevance, ensuring that a driver's response was possible within the given situational and temporal constraints. Speech rate and pause durations were adjusted to optimise intelligibility as much as possible, allowing for clear comprehension even during cognitively demanding driving tasks.

### **Scales and Measures**

According to common practice (e.g., Cripps, 2017), Cronbach's alpha was interpreted as poor ( $.5 \leq \alpha < .6$ ), questionable ( $.6 \leq \alpha < .7$ ), acceptable ( $.7 \leq \alpha < .8$ ), good ( $.8 \leq \alpha < .9$ ), or excellent ( $\alpha \geq .9$ ) for all subjective measures. All items of the subjective measures were answered on a 6-point Likert scale ranging from 1 (completely disagree) to 6 (completely agree), if not stated otherwise.

#### *Driving Data*

In addition to total and average energy consumption (Wh), we analysed further behavioural driving metrics addressed in the explanatory information: the mean of throttle pedal positions, brake pedal positions, and speed (km/h), respectively. Each metric was averaged across the two repetitions in the experimental block. All metric values were z-standardised within each sector across participants prior to aggregation to account for structural differences between sectors. That is, we transformed individual observations into sector-specific z-scores per driving metric and then computed mean values across all sectors..

#### *Perceived Support of Mental Model within Action Regulation*

The perceived support of the *mental model* within action regulation (Moll, Banach, et al., 2025) was assessed via five items focusing on the extent to which the available information supports the *mental model* in the context of action regulation concerning the definition of *mental models* (Carroll & Olson, 1988): aspects of the system, knowing how, knowing why, expand or correct existing *mental model*, and consistency of *mental model* and experiences (i.e., completeness/richness of the *mental model*). The scale's internal consistency was acceptable ( $M$

= 4.0,  $SD = 1.3$ ,  $\alpha = .79$ ). The complete item versions are listed in *Table B1* (English) and *Table B2* (German) in Appendix B.

#### *Subjective (Verbalisable) Ecodriving Knowledge*

Verbalisable ecodriving knowledge and ecodriving knowledge were assessed before and after the driving simulator experiment.

Ecodriving knowledge was measured using a 4-item scale capturing participants' knowledge of context-specific efficiency-relevant cues (input), how to monitor whether they are driving in a maximally energy-efficient way (comparator), how to operate vehicle controls to drive efficiently in different situations (output), and why certain driving behaviours are energy-efficient (know-why). The internal consistencies of the ecodriving knowledge scale were good at pre-test ( $M = 2.7$ ,  $SD = 1.4$ ,  $\alpha = .82$ ) and questionable at post-test ( $M = 4.1$ ,  $SD = 1.2$ ,  $\alpha = .66$ ).

Verbalisable ecodriving knowledge was measured using a comparable 4-item scale (input, comparator, output, know-why), focusing on participants' ability to articulate this knowledge. The internal consistencies of the verbalisable ecodriving knowledge scale were good at the pre-test ( $M = 2.6$ ,  $SD = 1.3$ ,  $\alpha = .85$ ) and acceptable at the post-test ( $M = 3.7$ ,  $SD = 1.2$ ,  $\alpha = .79$ ).

#### *Perceived Support of Action Regulation*

The perceived support of action regulation (Moll, Banach, et al., 2025) was assessed using two perspectives: (1) usability dimensions based on ISO 9241-11:2018 (Effectiveness, Efficiency) and action confidence, and (2) information processing stages within action regulation (Carver & Scheier, 1981, 1982; International Organization for Standardization, 2018; Parasuraman et al., 2000; Powers, 1973; Wickens & Carswell, 2021). The usability-oriented approach assesses how well the system supports effective, efficient, and confident action regulation, while the action regulation approach focuses on the perceived support of individual cognitive information processing stages as a proxy for latent cognitive processes. The complete item versions are listed in *Table B3* (German) and *Table B4* (English) in Appendix B.

From the usability perspective, three subscales were used, each consisting of 5 items that relate to the information processing steps within action regulation: information acquisition, information analysis, decision selection, and action implementation. The internal consistencies of the subscales effectiveness ( $M = 4.3$ ,  $SD = 0.9$ ,  $\alpha = .83$ ), efficiency ( $M = 3.7$ ,  $SD = 1.1$ ,  $\alpha = .84$ ) and confidence ( $M = 4.2$ ,  $SD = 0.9$ ,  $\alpha = .87$ ) were good.

From the action regulation perspective, four means are computed across different usability dimensions (effectiveness, efficiency, and confidence). The internal consistencies of the subscales information acquisition (three items,  $M = 3.9$ ,  $SD = 1.0$ ,  $\alpha = .64$ ), information analysis

(six items,  $M = 4.1$ ,  $SD = 1.0$ ,  $\alpha = .82$ ), decision selection (three items,  $M = 4.3$ ,  $SD = 1.0$ ,  $\alpha = .76$ ), and action implementation (three items,  $M = 4.1$ ,  $SD = 1.1$ ,  $\alpha = .71$ ) were questionable to good.

#### *Subjective Information Processing Awareness*

The SIPA scale was adopted from Schrills et al. (2024) and consists of 6 items developed based on the different levels of situation awareness. SIPA refers to users' subjective perception of how a system supports their ability to perceive, comprehend, and predict its information processing. The internal consistency of the scale ( $M = 4.2$ ,  $SD = 1.0$ ) was good ( $\alpha = .84$ ).

#### *Driving Activity Workload*

The *Driving Activity Load Index* (DALI; Pauzié, 2008) assessed drivers' subjective mental workload while driving after the blocks. DALI is a modified version of the NASA-TLX, specifically adapted to the driving context. The scale captures drivers' subjective workload across six dimensions reflecting attentional effort, perceptual and temporal demand, interference, and situational stress during the task. Participants rated each item on a six-point Likert scale ranging from 0 (low) to 5 (high), indicating the perceived intensity of each workload dimension. Higher scores represent a greater perceived workload in the respective domain. The scale's internal consistency was acceptable after the experimental block ( $M = 3.4$ ,  $SD = 1.7$ ,  $\alpha = .74$ ).

#### *Usage Pattern*

A separate set of six items was included to explore how participants in the *explanatory* condition used the recommendation display in conjunction with auditory explanatory tips. These items captured different strategies for integrating visual and auditory feedback, distinguishing between reliance on one source versus a combined approach. Results are descriptively reported per item.

### **Procedure**

Participants were randomly assigned to one of three groups using block randomisation (Mattis & Lachin, 1988), with four blocks containing ten slots per group: *control* group ( $n_1 = 36$ ), *recommendation* group ( $n_2 = 39$ ), and *explanatory* group ( $n_3 = 37$ ).

After the participants had read and signed the privacy policy and declaration of consent, they filled in a questionnaire to assess socio-demographic information, driving experience, experience with driving simulators, pre-existing technical and (verbalisable) ecodriving knowledge, and ecodriving motivation. Participants adjusted the seat position and steering wheel height so that all the displays were visible and the pedals could be reached comfortably.

Throughout the experiment, participants were provided with video instructions explaining the driving simulator, the experimental procedure, the experiment rules, and their tasks. Before the actual experiment, participants familiarised themselves with the driving simulation and the experiment rules during a 4-minute acclimatisation drive that included various manoeuvres, speed limits, curves, and hills. Participants received feedback on compliance with the traffic rules, particularly driving through stop signs and disregarding the speed limits, based on a visualisation of both the respective maximum speed and the speed travelled by the participants. In a second acclimatisation drive, participants should familiarise themselves with different pedal positions (1–5%, 20%, 30%, 40%) of the accelerator pedal. Understanding and practising specific pedal positions is essential for implementing energy-efficient driving strategies in electric vehicles, as subtle differences in accelerator input can significantly influence regenerative braking, energy consumption, and vehicle dynamics. First, participants were allowed to use a percentage display of the pedals' position to familiarise themselves with the pedal interaction. Second, participants drove a simple, straight route for two minutes. Every 10 seconds, they were verbally instructed to adopt one of the four predefined pedal positions. Participants were required to reach the position without using the display. Once confident they had done so, they were permitted to check and, if needed, adjust their input using the display.

After both acclimatisation drives, the main driving experiment consisted of two blocks: a baseline block and an experimental block. Each block included two test driving sectors followed by seven main driving sectors (see Figure 2). Both blocks began with the two test sectors, which allowed participants to practice the tasks and rules. Data from these sectors were not included in the analysis.

Participants were instructed to drive energy-efficiently, comply with traffic regulations, and follow road signs leading to the fictional city of *Simnitz* to avoid navigational errors. In the baseline block, only speed and gear selection were displayed. Each of the seven main driving sectors was completed once in randomised order. Participants answered the DALI questionnaire after completing the baseline block.

Figure 2

## Main Driving Sectors



Before the experimental block, participants were introduced to their assigned ecodriving feedback approach. The two test sectors were then completed again to familiarise participants with the new information, which was now available during driving. In the experimental block, all participants saw the conventional consumption display (see Figure 1). In addition, the *recommendation* and *explanatory* groups received optimal speed recommendations, while the *explanatory* group also received the auditory context-sensitive, rule-based tips during relevant situations. The groups were instructed to focus either on the conventional consumption display (*control* group), on the visual recommendation display suggesting optimal speeds (*recommendation* group) or also on additional auditory explanatory feedback in the form of rule-based tips (*explanatory* group). Each main driving sector was completed twice consecutively, again in randomised order.

After completing the experimental block, participants filled out several questionnaires, including measures of perceived (verbalisable) ecodriving knowledge, perceived support of action regulation, perceived support of the *mental model* within action regulation, the DALI, and the SIPA. They also provided a subjective evaluation of their respective ecodriving feedback approach and answered questions on sociodemographic characteristics. The complete experimental procedure took approximately 105 minutes per participant.

## 8.5. Results

For all analyses, the threshold of  $\alpha$  was set to .05, and effect sizes were interpreted according to Bühner (2021) and Cohen (1988, 1992). Small effects were defined as  $\eta^2 = .01$ ,  $V = r = 0.10$ , and  $d = 0.20$ ; moderate effects as  $\eta^2 = .06$ ,  $V = r = 0.30$  and  $d = 0.50$ ; and large effects as  $\eta^2 = .14$ ,  $V = r = 0.50$ , and  $d = 0.80$ . All analyses were performed in R (R Core Team, 2024) using RStudio (Posit Team, 2025). The R packages *stats* (R Core Team, 2024), *emmeans* (Lenth, 2024), *rstatix* (Kassambara, 2023), *car* (Fox & Weisberg, 2024) and *cofad* (Titz & Burkhardt, 2021, 2024) were used, amongst others.

Statistical assumptions for the applied parametric tests were evaluated before analysis. Normality of residuals and variance homogeneity were checked with the Shapiro–Wilk test (Shapiro & Wilk, 1965) and Levene’s test (Levene, 1960). In case of violated normality assumption, Kruskal–Wallis tests (Kruskal & Wallis, 1952) were conducted for metric variables and Pearson’s chi-square test (Agresti, 2007; Pearson, 1900) for categorical variables (gender, education). While most research questions were non-directional, we applied contrast analyses to test H1 and H2, as there was a clear directionality. We followed the recommended steps for contrast analysis outlined by Rosenthal et al. (2000). Descriptive statistics of the subjective scales and the z-standardised driving metrics can be found in *Table C1* in Appendix C.

No significant group differences were observed for total driving experience (km), BEV driving experience (km), age, gender, education, ecodriving motivation (eight items adapted from previous work of the research group and Arend & Franke, 2017), or affinity for technology interaction (Franke et al., 2019),  $p > .05$ . The groups can thus be considered comparable in this regard.

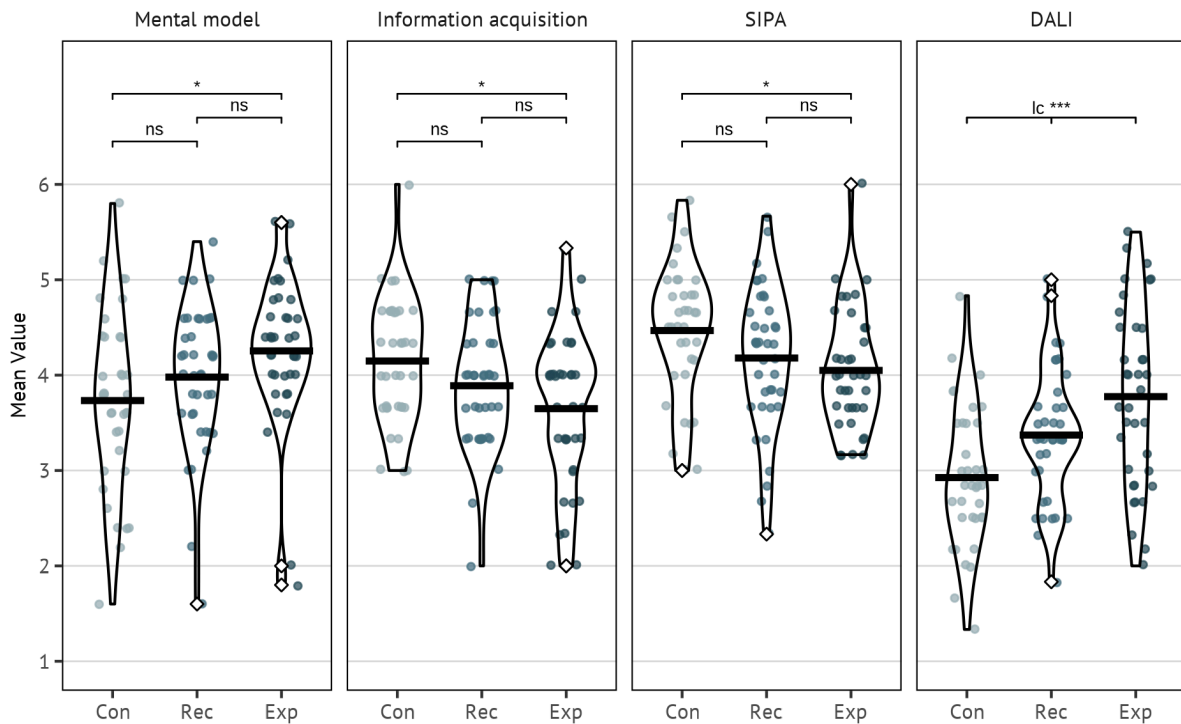
### Perceived Support of the Mental Model within Action Regulation (RQ1)

Regarding **RQ1**, a one-way ANOVA revealed a significant effect of the group on perceived support of the *mental model* within action regulation,  $F(2, 109) = 3.66$ ,  $p = .029$ ,  $\eta^2 = .06$  (moderate effect; see Figure 3).

Post hoc comparisons using Bonferroni-adjusted  $p$ -values showed that participants in the *explanatory* group ( $M = 4.3$ ,  $SD = 0.8$ ) reported significantly higher support of the *mental model* within action regulation than those in the *control* group ( $M = 3.7$ ,  $SD = 0.9$ ),  $p = .024$ ,  $d = 0.63$  (moderate effect). Participants in the *recommendation* group did not differ significantly from those in both the *control* group ( $p = .596$ ,  $d = 0.30$ , small effect) and those in the *explanatory* group ( $p = .447$ ,  $d = 0.33$ , small effect).

Figure 3

Support of the Mental Model, Support of Information Acquisition, SIPA, and DALI Across Groups (N = 112)



Note. The solid lines represent the group-specific means. Outliers, defined as values more than  $1.5 \times \text{IQR}$  below Q1 or above Q3, are indicated by white diamonds. Con = control, Rec = recommendation, Exp = explanatory.

\*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ , ns = not significant, lc = linear contrast.

### (Verbalisable) Ecodriving Knowledge (RQ2)

Regarding **RQ2**, two  $2 \times 3$  mixed ANOVAs were conducted on subjective (verbalisable) ecodriving knowledge to examine differences across time (pre-test vs. post-test) and group (*control*, *recommendation*, *explanatory*).

Regarding subjective ecodriving knowledge, there was a significant main effect of time,  $F(1, 218) = 119.64$ ,  $p < .001$ ,  $\eta^2 = .35$  (large effect), indicating that participants' ecodriving knowledge increased from pre- to post-test. No significant main effect of group,  $F(2, 218) = 0.43$ ,  $p = .652$ ,  $\eta^2 < .01$  (small effect), or group  $\times$  time interaction,  $F(2, 218) = 0.44$ ,  $p = .643$ ,  $\eta^2 < .01$  (small effect), were found. Post hoc comparisons using Bonferroni-adjusted  $p$ -values showed significant increases in subjective ecodriving knowledge from pre- to post-test in all three groups ( $ps < .001$ ), with large effect sizes in the *control* ( $d = 1.38$ ), *recommendation* ( $d = 1.37$ ), and *explanatory* ( $d = 1.64$ ) groups.

Similarly, a 2×3 mixed ANOVA on subjective verbalisable ecodriving knowledge revealed a significant main effect of time,  $F(1, 218) = 69.27, p < .001, \eta^2 = .24$  (large effect), indicating that participants' subjective verbalisable ecodriving knowledge increased from pre- to post-test. No significant main effect of group,  $F(2, 218) = 0.99, p = .375, \eta^2 = .01$  (small effect), or group × time interaction,  $F(2, 218) = 0.73, p = .485, \eta^2 < .01$  (small effect), were found. Post hoc comparisons using Bonferroni-adjusted  $p$ -values revealed significant pre–post increases in verbalisable ecodriving knowledge in all three groups ( $ps < .001$ ), with large effect sizes in the *control* ( $d = 1.04$ ), *recommendation* ( $d = 0.97$ ), and *explanatory* ( $d = 1.34$ ) conditions.

Overall, all groups showed comparable increases from pre- to post-test in both perceived ecodriving knowledge and verbalisable ecodriving knowledge. Descriptive statistics can be found in *Table C1* in Appendix C.

### Perceived Support of Action Regulation (RQ3)

Regarding **RQ3**, a series of one-way ANOVAs examined group differences in usability dimensions and information processing stages within action regulation.

Regarding usability, no significant group differences were found in perceived effectiveness,  $F(2, 109) = 1.34, p = .265, \eta^2 = .02$ ; efficiency,  $F(2, 109) = 2.14, p = .122, \eta^2 = .04$ ; or confidence,  $F(2, 109) = 1.42, p = .247, \eta^2 = .03$ . Similarly, for perceived support of information processing, there were no significant group differences for information analysis,  $F(2, 109) = 0.65, p = .526, \eta^2 = .01$ ; decision selection,  $F(2, 109) = 0.82, p = .444, \eta^2 = .01$ ; or action implementation,  $F(2, 109) = 0.92, p = .401, \eta^2 = .02$ . All non-significant effects on perceived usability and information processing stages were associated with small effect sizes ( $\eta^2 \leq .04$ ).

As visualised in Figure 3, however, there was a significant group effect for perceived support of information acquisition,  $F(2, 109) = 4.44, p = .014, \eta^2 = .08$  (moderate effect). Post hoc comparisons using Bonferroni-adjusted  $p$ -values revealed that participants in the *explanatory* group ( $M = 3.7, SD = 0.8$ ) perceived significantly lower support than the *control* group ( $M = 4.2, SD = 0.7$ ),  $p = .011, d = 0.70$  (moderate effect). The comparisons between *control* and *recommendation* groups ( $p = .361, d = 0.36$ , small effect) as well as between *recommendation* and *explanatory* groups ( $p = .441, d = 0.34$ , small effect) were not statistically significant.

### Subjective Information Processing Awareness (RQ4)

Regarding **RQ4**, a one-way ANOVA revealed a significant group effect on SIPA,  $F(2, 109) = 3.42, p = .036, \eta^2 = .06$  (moderate effect; see Figure 3). Post hoc comparisons using Bonferroni-adjusted  $p$ -values indicated that participants in the *explanatory* group ( $M = 4.1, SD = 0.6$ ) reported

significantly lower SIPA scores than those in the *control* group ( $M = 4.5$ ,  $SD = 0.7$ ),  $p = .036$ ,  $d = 0.60$  (moderate effect). The differences between the *control* group and *recommendation* group ( $p = .232$ ,  $d = 0.41$ , small effect) and between the *recommendation* group and *explanatory* group ( $p > .999$ ,  $d = 0.19$ , small effect) were not significant with small effect sizes.

### Driving Activity Workload (H1)

To test **H1**, we applied a contrast analysis with contrast weights assigned based on group (*control* =  $-1.5$ , *recommendation* =  $0.5$ , *explanatory* =  $1$ ). This contrast tested the hypothesis that DALI scores would be highest in the *explanatory* condition and lowest in the *control* condition. The analysis yielded a statistically significant contrast,  $F(1, 109) = 18.73$ ,  $p < .001$ , with an effect size of  $r = .38$  (moderate effect). DALI scores were highest in the *explanatory* group ( $M = 3.8$ ,  $SD = 1.0$ ), followed by the *recommendation* group ( $M = 3.4$ ,  $SD = 0.7$ ), and lowest in the *control* group ( $M = 2.9$ ,  $SD = 0.7$ ). These results support **H1** and are visualised in Figure 3.

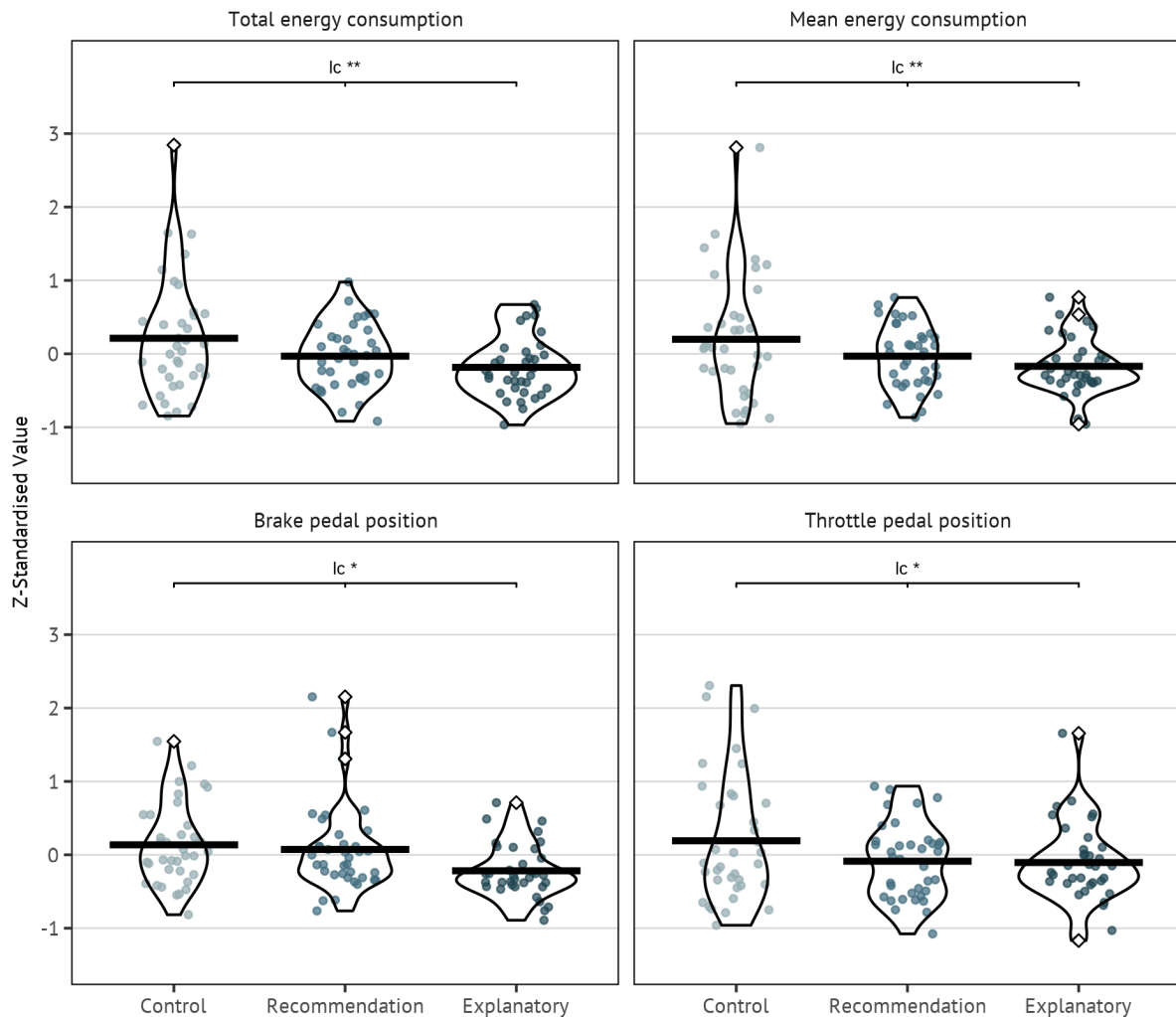
### Driving Performance (H2)

To test **H2**, we applied contrast analyses with contrast weights assigned based on group (*control* =  $1.5$ , *recommendation* =  $-0.5$ , *explanatory* =  $-1$ ). This contrast tested the hypothesis that performance would be best in the *explanatory* group and worst in the *control* group. Better performance was defined as lower values across the driving metrics, including consumption, speed, brake and throttle usage. All contrast analyses were conducted on data from the experimental block. For mean energy consumption, the contrast was significant,  $F(1, 105) = 7.14$ ,  $p = .009$ , with an effect size of  $r = .25$ . Similarly, total energy consumption showed a significant contrast,  $F(1, 105) = 8.28$ ,  $p = .005$ ,  $r = .27$ . For brake pedal position, the contrast also reached significance,  $F(1, 105) = 5.77$ ,  $p = .018$ ,  $r = .22$ . Finally, for throttle pedal position, the contrast was also significant,  $F(1, 105) = 4.47$ ,  $p = .037$ ,  $r = .20$ . Effect sizes were small to moderate.

These results indicate significant differences between the conditions concerning the tested contrast weights in favour of the *explanatory* condition regarding total energy consumption, mean energy consumption, mean brake pedal position, and mean throttle pedal position (see Figure 4). Descriptive statistics for the z-standardised driving metrics are provided in *Table C1* in Appendix C. However, for mean speed, the contrast was not significant,  $F(1, 105) = 2.09$ ,  $p = .151$ ,  $r = -.14$ , respectively. This indicates no meaningful differences between the conditions based on the tested contrast weights. Overall, **H2** can be partially supported.

**Figure 4**

*Ecodriving Performance in the Experimental Block (N = 109)*



*Note.* The solid lines represent the group-specific means. Outliers, defined as values more than  $1.5 \times \text{IQR}$  below  $Q_1$  or above  $Q_3$ , are indicated by white diamonds. \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ , lc = linear contrast.

### Usage Pattern of Explanatory Feedback and Recommendation Display

Participants' self-reported usage patterns were examined in more detail to explore the interaction between the auditory tips and the recommendation system beyond the predefined research questions. Participants in the *explanatory* condition ( $n_3 = 37$ ) reported diverse strategies combining the auditory rule-based tips and the recommendation display to drive as energy-efficiently as possible.

A clear majority (92%) agreed that they used the tips in addition to the recommendation display to maximise energy efficiency, and 78% used the tips as an explanatory aid for the recommended speed. 65% reported situational switching, stating they paid more attention to either the tips or the recommendation display depending on the context. A smaller share (57%) reported using only the recommendation display, while 51% stated they used it to verify whether they were correctly applying the auditory tips. Only 5% agreed with “I only used the tips,” indicating that relying exclusively on auditory tips was extremely rare. These findings suggest that participants predominantly preferred a complementary use of auditory tips and recommendation display, with few relying on just one of the two sources. The data also highlights a notable degree of adaptive use depending on the driving context.

## 8.6. Discussion

### Summary of Results

The present study examined how different feedback approaches—namely, a conventional consumption display, a recommendation display of optimal speed, and an enhanced version with auditory explanatory feedback in the form of tips—affect various outcomes related to driver cognition, experience, and performance. Specifically, we assessed their impact on drivers’ perceived support of the *mental model*, ecodriving knowledge, support of action regulation, SIPA, DALI, and objective driving performance. By comparing these feedback approaches, we aimed to identify which most effectively fosters adequate mental representations and ultimately supports energy-efficient driving behaviour.

Regarding **RQ1**, a significant effect of the feedback approach was found on the perceived support of the *mental model* within action regulation. Only participants in the *explanatory* condition reported significantly higher perceived support than those in the *control* condition, with a moderate effect size. The *recommendation* condition did not differ significantly from either the *control* or *explanatory* conditions, although small effects were observed.

Regarding **RQ2**, for (verbalisable) subjective ecodriving knowledge, all groups showed significant improvements from pre- to post-test with large effect sizes, indicating substantial learning gains. The *explanatory* group showed the largest effect sizes ( $d = 1.34/1.64$ ), suggesting potentially stronger intervention effects that may warrant further investigation with higher-powered samples. However, no significant differences emerged between the feedback conditions, nor were there significant group  $\times$  time interactions. This suggests that knowledge improvements occurred similarly across all groups, regardless of the feedback approach.

Regarding **RQ3**, no significant group differences were observed in usability dimensions (effectiveness, efficiency, and confidence) or support of later information processing stages (information analysis, decision selection, and action implementation). However, perceived support of information acquisition differed significantly between groups. Participants in the *explanatory* condition reported significantly lower support than those in the *control* group. No significant differences were found between the other groups.

Regarding **RQ4**, a significant effect of the feedback approach was found on SIPA scores. Participants in the *explanatory* group reported lower SIPA than the *control* group, with a moderate effect. Again, the *recommendation* condition did not differ significantly from the other groups.

**H1** could be accepted, as DALI scores were highest in the *explanatory* condition and lowest in the *control* condition, indicating that the driving activity workload was indeed greatest when additional auditory rule-based feedback was provided.

**H2**, which predicted the highest ecodriving performance in the *explanatory* condition (i.e., lower consumption and smoother driving indicated by less intense brake and throttle use) and the lowest in the *control* condition, received support. Significant contrasts were found for mean and total energy consumption, as well as for mean brake and throttle pedal positions, all favouring the *explanatory* condition. However, no significant contrast was found for mean speed, indicating that improvements did not extend to all driving metrics.

### **Theoretical and Practical Implications**

Most notably, the *explanatory* condition yielded the best performance, both in terms of pedal interaction patterns and energy consumption. This finding extends prior evidence on energy-saving benefits of standalone ecodriving recommendation systems (Allison et al., 2019), static, knowledge-based *know-how-and-why* tips (Moll, Banach, et al., 2025; Sureth et al., 2019), and applied previously discussed benefits of XAI (e.g., Arrieta et al., 2019; Gomez et al., 2023; Miller, 2019, 2023; Tiddi & Schlobach, 2022; Vilone & Longo, 2021) in the context of ecodriving. Besides performance benefits, drivers in the *explanatory* condition reported significantly greater support of their *mental model* compared to the control group, suggesting enhanced cognitive integration of the feedback. Integrating real-time explanatory information fosters deeper understanding and more consistent behavioural adaptation during driving, addressing previously observed gaps in drivers' knowledge (Moll, Heidinger, et al., 2025). By explicitly linking recommended actions with their underlying rationale, explanatory feedback may support the formation of more robust *mental models*, enhancing both momentary decisions and overall strategy adherence. This has practical implications for designing in-vehicle interfaces: systems that not only guide but also explain may be more effective in promoting

sustainable driving behaviour in real-world contexts. While drivers in the *explanatory* condition reported significantly greater support of their *mental model*, all conditions showed significant increases in self-reported ecodriving knowledge. This indicates that observing clear differences in knowledge gains between conditions may require longer exposure and more interaction to allow drivers to consolidate and confidently reflect on their learning in line with previous findings, with no significant improvements in ecodriving knowledge even after seven hours of training (Sullman et al., 2015). Interestingly, although the *explanatory* group exhibited clear advantages in objective driving performance and perceived support of their *mental model*, perceived support of action regulation within the various usability dimensions did not significantly differ between feedback approaches. This finding suggests that perceived usability may not fully align with measurable behavioural improvements. While usability affects acceptance and performance (e.g., Morris & Dillon, 1997; Van Schaik & Ling, 2011), actual performance may have an even greater impact on acceptance and trust (e.g., Wanner et al., 2022). This divergence between subjective experience and objective behaviour underscores the importance of assessing both dimensions. Future research should further explore the interplay between user experience and performance in the context of BEV, particularly to understand how these aspects relate to long-term acceptance and the sustained use of ecodriving support systems.

Furthermore, the observed reduction in SIPA scores and perceived support of information acquisition, as well as increased DALI scores, suggest that the alignment between the recommendation system and the additional auditory tips may not yet be optimal. This generally does not align with findings that explanatory information increases SIPA. Still, it might be possible that in the high-frequency and demanding real-time driving context, more frequent interactions are needed for the effects of information disclosure (i.e., explanatory tips) to become apparent (Schrills & Franke, 2023). While increased cognitive load might have undermined information acquisition and the development of ecodriving knowledge, prior research has noted that ecodriving information is inherently distracting in driving contexts (Allison & Stanton, 2019; Kircher et al., 2014). Future research should therefore move beyond the question of whether explanatory information distracts and instead investigate when and under which conditions it does so, for instance, during high-load manoeuvres or in time-critical situations. Understanding this temporal and situational sensitivity is key to designing interfaces that balance informativeness with cognitive efficiency.

Even though most participants reported using the recommendation display and the explanatory information, further open feedback also underlines challenges in the current system implementation: (a) uncertainty due to the non-transparent information acquisition and

analysis, (b) technical improvement potential of the recommendation system, and (c) amount of information.

Regarding the (a) non-transparent information acquisition and analysis by the recommendation system, a notable issue might be a mismatch between system recommendations and drivers' subjective comfort zones (see *Comfort Zone Model*; Summala, 2007). Some participants expressed uncertainty about the system's suggested speeds, particularly when recommendations incorporated route information not directly perceivable by the driver: "I felt unsure at times because the optimal speed display considered the course of the route, which I could not see. I wouldn't take a curve so fast if I couldn't see it." This highlights a critical limitation in the system's transparency and drivers' trust.

Technical and design issues (b) further complicated the user experience. Participants reported unexpected visual artefacts, such as the optimal speed display appearing "rectangular" unexpectedly, and suggested that current speed indicators on the display could be more salient to reduce the gaze frequency. These design shortcomings might have increased cognitive demands and contributed to frustration, which is detrimental in high-stakes driving contexts. Regarding the (c) amount of information, several participants found the tips excessively repetitive and, in some cases, distracting, especially when delivered during moments requiring high attention: "The auditory tips were sometimes distracting and came at times when I could not pay attention to them, potentially hindering concentration." This suggests that the timing and frequency of auditory cues need refinement to avoid cognitive overload and maintain driver focus. Visual distractions were also mentioned, with some participants feeling that the recommendation display diverted attention from critical traffic situations and reduced perceived driving safety. Thus, the present results offer concrete starting points for refining explanatory feedback. One promising direction is to enhance the adaptivity of the tips, for instance, by selectively triggering feedback based on actual driving deviations or systematic behavioural patterns. In parallel, alternative non-verbal representations of input-output relations could be explored to improve system transparency and foster users' understanding of the vehicle's logic and situational assessment. Future designs could also consider the prior association of verbal tips with simpler auditory cues to mitigate cognitive demands during critical manoeuvres. These cues could then be deployed independently and more proximally to relevant driving actions, allowing timely reminders at a lower processing cost.

Taken together, these findings reveal the inherent tension in designing explanatory feedback systems that effectively support energy-efficient driving and *mental model* building without increasing cognitive load or compromising information processing awareness. Future research should examine whether the observed "costs" of explanatory feedback, such as increased cognitive load or reduced support of information acquisition, are merely short-term side effects

and whether longer-term benefits in performance and *mental model* development may ultimately outweigh them. Building on the current findings, targeted hypotheses should further explore the interplay between knowledge acquisition, perceived support of the *mental model*, and actual improvements in action regulation.

### Limitations

Several limitations should be acknowledged when interpreting the present findings. First, although the study was conducted in a high-fidelity driving simulator with realistic route features, generalisability to real-world driving conditions remains limited. External factors such as varying traffic, environmental unpredictability, and social context were not represented and may significantly modulate how explanatory feedback is perceived and utilised.

Second, auditory tips' spatial and temporal placement was artificially controlled and not dynamically adapted to each driver's momentary cognitive load or environmental demands. While this was necessary to ensure comparability across conditions, it restricted the system's responsiveness and may have contributed to moments of distraction or redundancy.

Third, the integration between the visual recommendations and the auditory explanatory tips was not fully harmonised. Some participants reported mismatches that created confusion (e.g., "The auditory tips (...) gave me a feeling in some situations that my driving behaviour was wrong, although the optimum speed display was perfectly balanced."). In the current implementation, the tips were presented shortly before the visual recommendations became situationally relevant, to allow drivers to process and prepare for the suggested actions in advance. Moreover, the auditory tips focused more strongly on pedal interactions, aiming to provide regulatory support by clarifying how to achieve the visually indicated target speed. While this separation of functions was intentional, it may also have contributed to a misalignment between modalities, both in terms of timing and conceptual reference, which could have weakened the perceived coherence of the system and, in some cases, reduced drivers' trust in the feedback.

Fourth, the characteristics of the existing routes posed constraints on the fine-tuning of auditory tips. It was not always possible to optimise tip presentation—for example, by extending temporal spacing, delivering them earlier in the driving sequence, or adjusting prosody (speech rate, pauses) for clarity—without interfering with other aspects of the driving task.

Fifths, while the analysis focused on some behavioural performance metrics, more specific metrics, such as the proportion of time spent neutral gliding, using regenerative braking, or

mean pedal position for acceleration manoeuvres, could allow for a more precise rule-specific evaluation and a better mapping between system feedback and user behaviour. To achieve this, a robust manoeuvre classification would be required.

Finally, the sample consisted predominantly of younger participants, who were generally less experienced in driving yet had ATI scores above the scale midpoint. While this aligns with a target demographic increasingly exposed to advanced driver assistance systems, it limits the applicability of the findings to broader driver populations, including those with more driving experience or lower levels of ATI.

## 8.7. Conclusion

This study investigated the differential impact of three feedback approaches—conventional consumption display, recommendation display, and a recommendation display with auditory explanatory tips—on driver cognition, experience, and performance in energy-efficient driving in a high-fidelity simulator. The findings demonstrate that integrating auditory explanatory tips alongside visual speed recommendations significantly enhances drivers' perceived support of their *mental models* and leads to measurable improvements in energy consumption and pedal interaction. This underscores the potential of explanatory, multi-modal feedback to foster deeper cognitive integration and more effective behavioural adaptation than conventional systems. However, despite these promising benefits, the results also reveal important challenges (e.g., increased driving activity load, lower support of information acquisition, reduced information processing awareness), highlighting the inherent tension in balancing informativeness and cognitive efficiency in driver assistance design. Moreover, observed improvements in ecodriving knowledge were consistent across conditions, suggesting that more prolonged exposure and interaction may be necessary to detect distinct knowledge gains attributable to explanatory feedback. Practical implications emphasise the importance of adaptive feedback timing, greater transparency, and better integrating different feedback approaches to reduce distraction and enhance trust. Future research should investigate context-sensitive delivery of explanatory feedback and employ detailed behavioural metrics, alongside longer-term experience and consolidation, to clarify whether the benefits ultimately outweigh the costs or whether the latter diminish over time, thereby better elucidating the relationship between knowledge, *mental models*, cognitive load, and sustainable driving performance. In summary, explanatory multi-modal feedback is promising for advancing energy-efficient driving support, but further work is required to harmonise cognitive demands with information richness and confirm longer-term benefits in diverse real-world contexts.

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## 8.10. Appendix

### Appendix A: Previous Research

**Table A1**

*Summary of Previous Research with Tip-Based Ecodriving Recommendations*

Resource	Research objectives & tip example	Study design & vehicle technology	Feedback timing	Feedback modalities	Effect on consumption
Van der Voort et al. (2001)	<ul style="list-style-type: none"> <li>Evaluating a prototype fuel-efficiency support tool, quantifying its contribution to fuel savings compared to unaided ecodriving, and examining secondary effects of its implementation like time-to-collision.</li> <li><b>Example:</b> "Shift earlier from 2nd -&gt; 3rd"</li> </ul>	<ul style="list-style-type: none"> <li><math>N = 88</math></li> <li>simulator</li> <li>within-subject (runs); between-subject (group)</li> <li><b>ICEV</b></li> </ul>	real-time, dynamic	visual; text and colour signal	9–23%
Azzi et al. (2011)	<ul style="list-style-type: none"> <li>Assessing the contribution of verbal instructions to ecodriving performance, quantifying the additional contribution generated by two ecodriving assistance systems (visual and haptic), measuring drivers' acceptance of haptic ecodriving assistance system.</li> <li><b>Example:</b> Driving with the verbal instruction not to exceed 2000 Rpm.</li> </ul>	<ul style="list-style-type: none"> <li><math>N = 28</math></li> <li>simulator</li> <li>within-subject (conditions), between-subject (group)</li> <li><b>ICEV</b></li> </ul>	real-time	visual, haptic, visual-haptic	5%*
Andrieu & Saint Pierre (2012)	<ul style="list-style-type: none"> <li>Compare effects of simple advices and ecodriving training on driving behaviour.</li> <li><b>Example:</b> "Shift up between 2.000 and 2.500 revolutions per minute"</li> </ul>	<ul style="list-style-type: none"> <li><math>N_{1/2} = 19/20</math></li> <li>field study</li> <li>within-subject (2 trips)</li> <li><b>ICEV</b></li> </ul>	between the trips	visual; rules and indicators for each tip	11.3%–13.5%

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**Table 1** (continued)

Resource	Research objectives & tip example	Study design & vehicle technology	Feedback timing	Feedback modalities	Effect on consumption
Rouzikhah et al. (2013)	<ul style="list-style-type: none"> <li>Examining the effects of an ecodriving message on driver distraction.</li> <li><b>Example:</b> “Your performance: High Fuel Consumption. Due to: Speeding and over deceleration”</li> </ul>	<ul style="list-style-type: none"> <li><math>N = 22</math></li> <li>simulator</li> <li>within-subject (scenarios)</li> <li><b>Power train not explicitly specified</b></li> </ul>	real-time	visual	no consumption analysed
Daun et al. (2013)	<ul style="list-style-type: none"> <li>Verifying the efficacy of the predictive EDAS and quantifying its fuel-saving potential</li> <li><b>Example:</b> “Please take your foot off the accelerator! Explanation: Rolling ahead of curve“</li> </ul>	<ul style="list-style-type: none"> <li><math>N = 41</math></li> <li>simulator</li> <li>within-subject (runs), between-subject (group)</li> <li><b>ICEV</b></li> </ul>	real-time (predictive) and retrospective	visual, auditory	6%
Zhao et al. (2015)	<ul style="list-style-type: none"> <li>Developing and validating an ecodriving feedback system to support ecodriving training</li> <li><b>Example:</b> “Please avoid accelerating rapidly”</li> </ul>	<ul style="list-style-type: none"> <li><math>N = 22</math></li> <li>simulator</li> <li>within-subject</li> <li><b>ICEV</b></li> </ul>	real-time and after driving; dynamic and static	auditory, verbal visual	3.43–5.45%
Wu et al. (2017)	<ul style="list-style-type: none"> <li>Comparing and evaluating the effects of ecodriving training (only static information vs. additional coaching) on different driving behaviours in start, stop, speed choice and no-idling</li> <li><b>Example:</b> “Avoid rapid starts and accelerate to 20 km/h using 5 s”</li> </ul>	<ul style="list-style-type: none"> <li><math>N = 22</math></li> <li>simulator</li> <li>within-subject</li> <li><b>ICEV</b></li> </ul>	before driving	visual, verbal	no consumption analysed
Beloufa et al. (2019)	<ul style="list-style-type: none"> <li>Examining different forms of knowledge transfer (video instruction vs. interactive guidance system).</li> <li><b>Example:</b> „Maintain constant speed when the road is clear.“ (Score: mean standard deviation in speed.)</li> </ul>	<ul style="list-style-type: none"> <li><math>N = 72</math></li> <li>simulator</li> <li>pre-post within-subject (scenario), between-subject (group)</li> <li><b>ICEV</b></li> </ul>	before driving (tips), real-time and retrospective	auditive/verbal, visual; static tip list, immediate visual or auditory cues, immediate and retrospective CO2 emission level	7.7%–12.4%

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**Table 1** (continued)

Resource	Research objectives & tip example	Study design & vehicle technology	Feedback timing	Feedback modalities	Effect on consumption
Günther et al. (2019)	<ul style="list-style-type: none"> <li>Examining the influence of pre-drive theoretical ecodriving training versus practical BEV driving experience on self-reported ecodriving behaviour, knowledge, knowledge certainty rating and ecodriving acceptance</li> <li><b>Examples:</b> Adhering to the speed limit, moderate acceleration when starting, consistent use of the regenerative braking</li> </ul>	<ul style="list-style-type: none"> <li><math>N = 63</math></li> <li>field study</li> <li>between-subject design (group)</li> <li><b>BEV</b></li> </ul>	training before driving	visual; theoretical training and tips	no consumption analysed
Sureth et al. (2019)	<ul style="list-style-type: none"> <li>Developing and testing concise textual ecodriving rules to improve knowledge and performance.</li> <li><b>Example:</b> “If you want to accelerate from standstill, then press the gas pedal to that extent, that you accelerate rather quickly to your desired speed with the combustion engine without intensive use of the electrical engine. The combustion engine runs particularly efficiently in the medium load range (when accelerating rather quickly without loud revving of the engine). By contrast, the active use of the electrical engine for acceleration from standstill consumes a lot of energy from the battery, which then has to be recharged over a long period. Thereby, many energy conversion losses emerge (inefficient).”</li> </ul>	<ul style="list-style-type: none"> <li><math>N = 81</math> (61 in analyses of fuel consumption)</li> <li>field study</li> <li>within-subject (pre, post)</li> <li>between-subject (group)</li> <li><b>HEV</b></li> </ul>	tip list before one-month test phase	visual; static tip list	4%
Moll, Banach, et al. (2025)	<ul style="list-style-type: none"> <li>Developing and testing textual BEV ecodriving rules to support mental model development and performance</li> <li><b>Example:</b> “If you want to reduce your speed, then avoid pressing down hard on the brake pedal and using the mechanical brake. If you press harder on the brake pedal, the mechanical brake is activated in addition to regenerative braking. As a result, the momentum energy is ultimately converted into heat and is therefore completely lost.”</li> </ul>	<ul style="list-style-type: none"> <li><math>N = 50</math> (47 in analyses of energy consumption)</li> <li>field study</li> <li>between-subject design (group)</li> <li><b>BEV</b></li> </ul>	tip list before driving	visual; static tip list	11.3%

*Note.* The articles are sorted in ascending order according to the year. ICEV = combustion vehicle, BEV = battery electric vehicle, HEV = hybrid electric vehicle. \* Reduced total polluting emissions compared to driving sessions without instructions.

## Appendix B: Scales

**Table B1**

*Support of the Mental Model within Action Regulation Scale in English*

No	Item text
1	... help me understand which aspects I need to consider to drive as energy-efficiently as possible.
2	... help me to understand how to drive in an energy-efficient way.
3	... help me understand why driving is energy-efficient in a certain way.
4	... allow me to improve my existing knowledge of energy-efficient driving.
5	... provide me with a complete knowledge of energy-efficient driving behaviour.

*Note.* Instruction text: “What role does the available information play in your understanding of how to drive as energy-efficiently as possible? By ‘available information’ we mean all information that relates to your goal (ecodriving), [especially the tips received and also] information from the vehicle and the environment. Please indicate your level of agreement with the following statements. The information available...”

**Table B2**

*Perceived Support of the Mental Model within Action Regulation Scale in German*

No	Item text
1	... helfen mir dabei zu verstehen, welche Aspekte ich berücksichtigen muss, um so energieeffizient wie möglich zu fahren.
2	... unterstützen mich dabei zu verstehen, wie man energieeffizient fährt.
3	... helfen mir dabei zu verstehen, warum es energieeffizient ist, auf eine bestimmte Art und Weise zu fahren.
4	... erlauben es mir, mein bestehendes Wissen über energieeffizientes Fahren zu verbessern.
5	... vermitteln mir ein vollständiges Wissen über energieeffizientes Fahrverhalten.

*Note.* Instruction text: „Welche Rolle spielen die verfügbaren Informationen bei Ihrem Verständnis darüber, möglichst energieeffizient zu fahren? Mit ‘verfügbaren Informationen’ meinen wir alle Informationen, die sich auf Ihr Ziel (energieeffizientes Fahren) beziehen, also [vor allem die erhaltenen Tipps und auch die] Informationen aus Fahrzeug und Umwelt. Bitte geben Sie den Grad Ihrer Zustimmung zu folgenden Aussagen an. Die verfügbaren Informationen...”

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**Table B3**

*Perceived Support of Action Regulation Scale in German*

Items	Usability	Information processing
... kann ich alle relevanten Informationen genau wahrnehmen.	1	Acq
... kann ich präzise feststellen, ob ich im Hinblick auf mein Ziel bestmöglich handle.	1	Ana
... kann ich Handlungsmöglichkeiten und deren Auswirkungen genau ableiten.	1	Ana
... kann ich optimal entscheiden, wie ich mein Handeln im Hinblick auf mein Ziel anzupassen habe.	1	Dec
... kann ich mein Handeln bestmöglich im Hinblick auf mein Ziel umsetzen.	1	Imp
... kann ich alle relevanten Informationen mühelos wahrnehmen.	2	Acq
... kann ich ohne Anstrengung feststellen, ob ich im Hinblick auf mein Ziel bestmöglich handle.	2	Ana
... kann ich Handlungsmöglichkeiten und deren Auswirkungen mühelos ableiten.	2	Ana
... kann ich schnell entscheiden, wie ich mein Handeln im Hinblick auf mein Ziel anzupassen habe.	2	Dec
... kann ich mein Handeln mühelos im Hinblick auf mein Ziel umsetzen.	2	Imp
... bin ich mir sicher, dass ich alle relevanten Informationen einbezogen habe, um mein Verhalten zu verbessern.	3	Acq
... fühle ich mich sicher dabei festzustellen, ob ich im Hinblick auf mein Ziel bestmöglich handle.	3	Ana
... fühle ich mich sicher, Handlungsmöglichkeiten und deren Auswirkungen abzuleiten.	3	Ana
... kann ich sicher entscheiden, wie ich mein Handeln im Hinblick auf mein Ziel anzupassen habe.	3	Dec
... fühle ich mich sicher darin, mein Handeln bestmöglich im Hinblick auf mein Ziel anzupassen.	3	Imp

*Note.* 1 = effectiveness, 2 = efficiency, 3 = confidence, Acq = information acquisition, Ana = information analysis, Dec = decision selection, Imp = action implementation. Instruction text: "Während Sie versuchen, möglichst energieeffizient zu fahren (= Ziel) können verschiedene kognitive Prozesse eine Rolle spielen, wie: auf relevante Informationen aus dem Fahrzeug oder der Umwelt achten; Kontrollieren, erkennen und verstehen, wie das Handeln vom Ziel abweicht; Handlungsmöglichkeiten ableiten und deren Vor- und Nachteile abwägen; für die optimale Handlungsmöglichkeit entscheiden und sie umsetzen. Zunächst geht es darum, wie [gut bzw. genau / mühelos / sicher] Sie das Ziel, energieeffizient zu fahren, mithilfe der verfügbaren Informationen erreichen konnten. Mit "verfügbaren Informationen" meinen wir [...]. Bitte geben Sie den Grad Ihrer Zustimmung zu folgenden Aussagen an. Mithilfe der verfügbaren Informationen..."

## Study 4: Explaining Ecodriving Recommendations

**Table B4**

*Perceived Support of Action Regulation Scale in English*

Items	Usability	Information processing
... can perceive all relevant information accurately.	1	Acq
... can determine precisely whether I am acting in the best possible way with regard to my goal.	1	Ana
... can accurately derive possible action options and their effects.	1	Ana
... can decide optimally how to adapt my actions with regard to my goal.	1	Dec
... can implement my actions in the best possible way with regard to my goal.	1	Imp
... can perceive all relevant information effortlessly.	2	Acq
... can determine without effort whether I am acting in the best possible way with regard to my goal.	2	Ana
... can effortlessly derive possible action options and their effects.	2	Ana
... can decide quickly how to adapt my actions with regard to my goal.	2	Dec
... can implement my actions effortlessly with regard to my goal.	2	Imp
... am sure that I have included all relevant information to improve my behaviour.	3	Acq
... feel confident in determining whether I am acting in the best possible way with regard to my goal.	3	Ana
... feel confident in deriving possible action options and their effects.	3	Ana
... can confidently decide how to adapt my actions with regard to my goal.	3	Dec
... feel confident in implementing my actions in the best possible way with regard to my goal.	3	Imp

*Note.* 1 = effectiveness, 2 = efficiency, 3 = confidence, Acq = information acquisition, Ana = information analysis, Dec = decision selection, Imp = action implementation. Instruction text: "While you are trying to drive as energy-efficiently as possible (= goal), various cognitive processes can play a role, such as: paying attention to relevant information from the vehicle or the environment; checking, recognising and understanding how action deviates from the goal; deriving possible options of action and weighing up their advantages and disadvantages; deciding on the optimal course of action and implementing it. Firstly, it is about how [well or accurately / effortlessly / confidently] you were able to achieve the goal of driving energy-efficiently using the information available. By 'available information' we mean [...]. Please indicate your level of agreement with the following statements. With the help of the information available, I..."

## Appendix C: Descriptive Results

Table C1

*Descriptive Results of the Subjective Scales and the Z-Standardised Driving Metrics*

Measure	Control	Recommendation	Explanatory
	<i>M (SD)</i>	<i>M (SD)</i>	<i>M (SD)</i>
<i>Perceived support of the mental model within action regulation</i>	3.73 (0.94)	3.98 (0.76)	4.25 (0.77)
<i>Perceived support of action regulation: usability</i>			
Effectiveness	4.27 (0.70)	4.48 (0.64)	4.23 (0.80)
Efficiency	3.94 (0.87)	3.67 (0.77)	3.54 (0.90)
Confidence	4.32 (0.77)	4.28 (0.60)	4.05 (0.80)
<i>Perceived support of action regulation: information processing</i>			
Information acquisition	4.15 (0.66)	3.89 (0.67)	3.65 (0.81)
Information analysis	4.14 (0.76)	4.12 (0.64)	3.97 (0.74)
Decision selection	4.29 (0.88)	4.39 (0.63)	4.16 (0.84)
Action implementation	4.18 (0.78)	4.19 (0.72)	3.96 (0.90)
<i>Ecodriving knowledge</i>			
pre-test	2.68 (1.26)	2.83 (1.05)	2.66 (1.03)
post-test	3.99 (0.89)	4.13 (0.75)	4.22 (0.60)
<i>Verbalisable ecodriving knowledge</i>			
pre-test	2.53 (1.11)	2.78 (1.09)	2.54 (1.02)
post-test	3.52 (0.92)	3.71 (0.80)	3.82 (0.75)
<i>Subjective Information Processing Awareness (SIPA)</i>	4.47 (0.71)	4.18 (0.75)	4.05 (0.63)
<i>Driving Activity Load Index (DALI)</i>	2.93 (0.74)	3.37 (0.69)	3.77 (0.95)
<i>Driving Performance (z-standardised)</i>			
Energy consumption (mean)	0.11 (0.74)	-0.05 (0.53)	-0.06 (0.51)
Energy consumption (total)	0.13 (0.68)	-0.05 (0.55)	-0.08 (0.48)
Throttle pedal position (mean)	0.1 (0.81)	-0.01 (0.64)	-0.08 (0.54)
Brake pedal position (mean)	0.08 (0.56)	-0.09 (0.49)	0.01 (0.65)
Speed (mean)	-0.07 (0.7)	0.01 (0.5)	0.06 (0.59)

*Note.*  $N = 112$  for subjective measures and  $N' = 109$  for driving performance.

## 9. General Discussion

This section integrates the empirical findings of the dissertation and situates them within broader theoretical and applied contexts. Section 9.1 discusses the theoretical implications regarding the ROs outlined in Section 3. Section 9.2 provides a critical methodological reflection on the research designs and empirical strategies employed across the studies. Section 9.3 summarises the dissertation's contributions—covering theoretical, methodological, conceptual-analytical, empirical, and applied aspects—to the field of engineering psychology.

### 9.1. Theoretical Implications

#### **RO1: How Do Different Feedback Approaches Influence Users' Perception, Judgements, and Implementation of Energy-Efficient Driving Strategies?**

Theoretically grounded in control-theoretic models of action regulation (Carver et al., 2015; Carver & Scheier, 1982, 1998, 2000; Powers, 1973), the studies addressed various aspects of the control loop, including judgements of strategies' energy efficiency as a central component of adaptive strategy selection in ecodriving (Franke et al., 2016). Driving performance is analogously regarded as a key variable for evaluating support for successful action regulation, consistent with previous ecodriving research.

**Study 1** established a systematic foundation by examining how accurately and adequately consumption values are perceived in conventional displays and how these perceptions inform efficiency judgments. An experimental paradigm was developed based on initial mathematically quantitative approaches (E. Wu et al., 2016) to address the gap between well-researched static data visualisation (e.g., Baird & Noma, 1978; Cleveland & McGill, 1984; Falmagne, 1971; Hollands & Spence, 1992; Stevens, 1957) and the underexplored domain of dynamic real-time data visualisation. In line with known biases in the driving context (e.g., Eriksson et al., 2015; Eriksson & Svenson, 2012; Larrick & Soll, 2008; Peer & Gamliel, 2013; Svenson, 1976, 2021; Svenson & Salo, 2010), differences in static fuel efficiency identifications depending on feedback approach (Rakauskas et al., 2010), and established heuristics of human information processing such as the availability heuristic (Tversky & Kahneman, 1973) and the peak-end rule (Fredrickson & Kahneman, 1993; Kahneman, 2000), this work contributed to understanding (heuristic) information processing by users of consumption displays. Although perfect estimations might not be necessary (*mental models* might be incomplete but potentially sufficient), individuals fail to rank different temporal dynamics regarding energy efficiency correctly. Furthermore, important groundwork was laid regarding interindividual differences

(e.g., ATI, knowledge) influencing systematic biases. This aligns with prior research on the need for cognition as a broader construct underlying ATI, which showed that higher levels of need for cognition are associated with higher cognitive engagement, better task performance, and potentially less reliance on heuristic information processing (e.g., Cacioppo et al., 1996; Cazan & Indreica, 2014; Dickhäuser et al., 2009; Rangannavar & Shahapur, 2018).

Building on these insights of Study 1, various alternative feedback approaches and their effects on driving performance were evaluated in **Studies 2 to 4**. Following previous reviews, ecodriving feedback approaches have frequently been evaluated against a condition with no information rather than against well-founded alternative conditions. To address this limitation, status quo conditions were also included, such as a consumption trace display in Study 2, generic tips in Study 3, and a conventional consumption display in Study 4. While Study 2 focused on feedback approaches that provide consumption values over time or more automated behavioural guidance (e.g., optimal speed recommendations), Studies 3 and 4 implemented feedback approaches designed to foster drivers' understanding, providing textual or auditory know-how- and-why information.

In line with previously reported effects on fuel consumption ranging from no effect up to 32.0% (Allison & Stanton, 2019; Dahlinger & Wortmann, 2016; Kurani et al., 2015; Sanguinetti et al., 2020), Study 2 revealed no significant consumption effect dependent on the feedback approach. Study 3 showed lowest consumption in the experimental *know-how-and-why* condition (11.3% lower average consumption than without support). Study 4 demonstrated feedback-approach-dependent effects, with participants in the explanatory feedback condition showing 9.1–15.6% lower average consumption than the other two conditions.

Corresponding to previous research incorporating behavioural driving performance metrics (e.g., Beusen et al., 2009; Birrell et al., 2014; Daun et al., 2013; Dib et al., 2014; Hibberd et al., 2015; Martin et al., 2013; Rolim et al., 2014; Savković, Gladović, et al., 2019; Stillwater & Kurani, 2014; Sullman et al., 2015; Y. Wu et al., 2017) and significant correlations between several driving pattern parameters and energy use in EV (A. Braun & Rid, 2018), Studies 2 to 4 included complementary behavioural indicators to more precisely assess the effects of feedback approaches—such as manoeuvre-specific tips or real-time displays—on distinct aspects of driving behaviour (e.g., proportion of regenerative braking or throttle position). Study 2 revealed differences between feedback conditions in braking-related behaviour (e.g., proportion of regenerative braking and mechanical braking) and constant-speed driving (e.g., mean speed), with participants receiving speed recommendations showing a higher proportion of regenerative braking and lower use of mechanical braking compared to those receiving a consumption trace display. Additionally, participants in the speed recommendation condition maintained lower average speeds than those who received no feedback, consistent with

findings from studies involving tips, training, or visual displays with speed trajectories or fuel economy (Daun et al., 2013; Dib et al., 2014; Martin et al., 2013; Stillwater & Kurani, 2014). However, no differences emerged depending on feedback approaches for neutral gliding and metrics in acceleration manoeuvres and the manoeuvre braking to standstill. Moreover, there was no consumption advantage in any feedback condition. In Study 3, selective behavioural effects were found: participants in the *know-how-and-why* condition demonstrated the lowest mean and variability in throttle position, while no significant differences emerged for other behavioural measures such as braking pedal pressure, or speed. Study 4 similarly showed selective effects on pedal positions, but not for speed, again in favour of the auditory *know-how-and-why* feedback approach compared to both the recommendation system and the conventional consumption display.

Together, these findings suggest that energy consumption effects are not necessarily mirrored by consistent behavioural effects, and vice versa. A single intervention of the examined feedback approaches might not be sufficient to produce uniform improvements across all behavioural and consumption-related dimensions. However, comprehension-based feedback—whether textual or auditory—tended to yield favourable outcomes in both consumption and behavioural metrics. This aligns with evidence from interventions targeting ICEVs and HEVs, where tips and training interventions have led to significant improvements in consumption and/or driving behaviour (e.g., Andrieu & Saint Pierre, 2012; Azzi et al., 2011; Beloufa et al., 2019; Jeffreys et al., 2018; Poolkrajang, 2024; Savković et al., 2020; Savković, Gladović, et al., 2019; Savković, Miličić, et al., 2019; Sullman et al., 2015; Sureth et al., 2019; van der Voort et al., 2001; Y. Wu et al., 2017, 2018; Zavalco, 2018; Zhao et al., 2015).

In summary, more elaborated, comprehension-oriented information appears to have beneficial effects on driving performance. However, the pattern of results across behavioural measures was not always consistent. At the same time, higher automated feedback approaches did not consistently improve performance compared to standard consumption displays, despite previously reported advantages over no-support baselines (Allison et al., 2019).

Future research should investigate the long-term effects of such feedback approaches, potentially allowing for longer consolidation phases or extended intervention periods. Furthermore, a deeper understanding of how explanatory information can be implemented effectively in combination with recommendation-based feedback systems is needed.

## **RO2: To What Extent Do Different Feedback Approaches Support Users' Understanding of Energy-Efficient Driving?**

RO2 investigated how different feedback approaches support users' understanding of energy-efficient driving. The underlying assumption is that effective ecodriving requires behavioural adaptation and adequate *mental models* that allow drivers to comprehend, anticipate, and generalise energy-efficient strategies. This becomes particularly important when complexity (i.e., task demand) increases—under such conditions, knowledge seems to be more important than motivation in determining ecodriving performance (Franke et al., 2016).

**Study 2** provided initial qualitative insights into users' ecodriving understanding based on experience with three feedback conditions: no information, a consumption trace display, and a speed recommendation display. While participants across all groups were familiar with basic ecodriving principles, such as smooth acceleration or gentle braking, this knowledge was often vague and lacked actionable specificity. More importantly, explanations rarely reflected technical or vehicle-specific reasoning. Critical concepts such as neutral gliding, engine efficiency, or aerodynamic drag were seldom mentioned and frequently misunderstood. Common misconceptions included inappropriate assumptions about acceleration intensity, confusion between gliding and regenerative braking, and incorrect inferences about pedal use and vehicle behaviour. These findings were reflected in low overall tip accuracy across all groups, with no significant differences. Thus, despite exposure to different feedback forms, participants generally failed to develop accurate and technically grounded ecodriving knowledge. This indicates that it is not sufficient to understand how existing knowledge can be activated (Pampel et al., 2017)—adequate *mental models* must be formed and refined through targeted support. The results are not comparable to the ICEV context, where drivers were shown to possess relatively good ecodriving knowledge (Lai, 2015). Instead, the current findings align with prior work regarding HEV drivers by Franke et al. (2016), who identified false beliefs that can lead to inefficient driving strategies. They also support the conclusion by Neumann and Kreams (2016) that BEV drivers lack a conceptual understanding of electrical units and BEV-specific energy dynamics.

**Study 3** addressed the identified knowledge gaps more directly by comparing the effects of generic ecodriving tips or know-how-and-why tips compared to no information before the driving task. Results demonstrated that the gain in perceived ecodriving knowledge was highest in the know-how-and-why condition. This finding aligns with prior evidence that a know-how-and-why tip list can significantly improve ecodriving performance (Sureth et al., 2019) and extends this insight to the BEV context. These results also go along with findings from Arend et al. (2019), emphasising the central role of the *know-why* component. In sum,

know-how-and-why tips strengthen drivers' perceived conceptual understanding of energy-efficient driving strategies.

**Study 4** further explored this promising know-how-and-why approach in a real-time feedback setting, examining its potential to enhance the explainability of system recommendations. Participants in all three experimental groups—conventional consumption display, speed recommendation system, and additional auditory know-how-and-why feedback—demonstrated a significant increase in (verbalisable) ecodriving knowledge over time. This suggests that repeated task engagement and feedback contribute to learning effects concerning perceived knowledge. When interpreted in light of Study 3, these findings suggest that the effectiveness of explanatory feedback critically depends on its integration within the driving task and in combination with other feedback formats. While prior studies involving auditory real-time prompts have demonstrated improvements in driving behaviour (Zhao et al., 2015), they did not assess knowledge, making direct comparisons to the present findings difficult.

Furthermore, forming and correcting *mental models* is cognitively demanding. As described in Section 2.2, *mental models* act as filters for new information, and updating them requires integrating novel inputs with existing beliefs—an inherently effortful process (Johnson-Laird, 1994, 2001, 2010; Jones et al., 2011). Also, Rasmussen (1983) emphasised that knowledge-based behaviour involves conceptual reasoning, mental simulation, and evaluation, all of which impose a high cognitive load. This aligns with Kircher et al. (2014), who argued that cognitively engaging ecodriving information may be unavoidably distracting in real-time contexts. Thus, the availability of cognitive resources is a crucial boundary condition for effective *mental model* formation and updating (Valadao et al., 2015). In fact, driving activity load was highest in the explanatory condition of Study 4, potentially limiting the impact of the additional feedback. The trade-off between explainability and cognitive overload may explain the absence of condition-specific effects. Additionally, Sullman et al. (2015) found no significant improvements in ecodriving knowledge even after seven hours of training, suggesting that meaningful knowledge elaboration may require sufficient time and motivation.

Moreover, the combination of speed recommendations and explanatory content may have introduced conflicting information, particularly for participants whose pre-existing *mental models* did not align with the system feedback. A few participants of Study 4 explicitly noted a mismatch between combined feedback or between the recommendations and their understanding, while describing discomfort or irritation when receiving advice they found implausible or inconsistent. Such mismatches can undermine willingness to engage cognitively, especially if the gap between task demands and perceived capabilities exceeds the individual tolerance thresholds (Fuller, 2005, 2011). Increased perceived difficulty and cognitive dissonance (Festinger, 1957; McGrath, 2017) may have interfered with *mental model* updating by

cognitive restructuring (e.g., “Perhaps accelerating with a driving pedal position of 30% is not always efficient after all.”) or triggering defensive responses such as discounting system information or resisting integration with existing beliefs, particularly in the explanatory condition. The higher amount of information, along with delayed and/or mismatched system recommendations following the tips, might have led participants to deprioritise cognitive engagement in favour of comfort and cognitive ease (Summala, 2007). A deeper understanding is required to determine whether driving activity load decreases over time as drivers gain experience and consolidate knowledge, as Neumann et al. (2015) showed that experience may lead to more differentiated knowledge. In line with expert performance research, a meaningful domain-specific competence typically requires several months of practical experience, with an extended period necessary to reach optimal levels of relevant knowledge and skills (Ericsson, 2006).

In sum, while users’ understanding of energy-efficient strategies is not sufficiently elaborated based on status quo information (i.e., conventional consumption displays), it can be significantly enhanced through comprehension-based feedback that explains both the *how* and *why* of such strategies. Its successful internalisation might depend on cognitive load, the degree of integration and information processing transparency between the comprehension-based feedback and other energy-related information, the resolution of *mental model* mismatches, as well as duration of consolidation.

### **RO3: How Do Different Feedback Approaches Influence Users’ Subjective Quality of Action Regulation?**

RO3 explored how different feedback approaches affect drivers’ subjective perception of support during energy-efficient driving. This dimension has often been neglected in ecodriving research, despite its relevance for the sustained use and acceptance. The subjective quality of action regulation captures how well drivers feel supported in effectively, efficiently and confidently regulating complex tasks, and integrating feedback into their behaviour. The perceived support of the *mental model* as well as perceived uncertainty due to a lack of knowledge highlight the system’s contribution to understanding and reducing uncertainty based on missing knowledge. Beyond measuring performance or knowledge acquisition, this perspective sheds light on the psychological experience of using ecodriving support systems, especially under varying task demands and informational conditions.

**Study 2** provided initial insights. Participants receiving clear target values (i.e., recommendations of optimal speed) consistently reported lower uncertainty, both across all driving manoeuvres and when accelerating from a standstill, compared to those who received

no support. This suggests that simple, prescriptive feedback can reduce perceived ambiguity in action regulation, even without improving conceptual understanding (see RO2) or energy consumption (see RO1). No significant uncertainty reduction was found when comparing the consumption display with no feedback. This raises cautious questions about the objective utility of such feedback (see RO1) and the subjective quality of drivers' action regulation.

**Study 3** extended the analysis by systematically comparing how different types of tip-based information affected perceived support across and within distinct information processing stages. In line with expectations, participants in the *know-how-and-why* condition reported the highest levels of support for effective, efficient, and confident action regulation, information acquisition, information analysis, and action implementation. However, no significant linear contrast emerged for decision selection, partially contradicting expectations. However, the *know-how-and-why* group felt best supported in their *mental model*, with the group receiving no tips reporting the lowest values. Although participants reported significantly higher perceived support of the *mental model*, this did not translate into lower perceived uncertainty or greater subjective confidence in action regulation. This is consistent with findings that gaining knowledge can increase awareness of domain complexity and reduce (over-)confidence, especially in unfamiliar environments (Jaspan et al., 2022; Lejarraga & Lejarraga, 2020). The dissociation suggests that while feedback approaches may foster understanding, confident decision selection and reduced uncertainty likely depends on deeper experience and iterative feedback (Li et al., 2005; Parker, 2005).

**Study 4** investigated real-time feedback and confirmed some of these trends. A significant effect of the feedback approach was found for *mental model* support: participants in the explanatory condition with additional auditory know-how-and-why tips reported higher perceived support compared to only status-quo consumption information. Interestingly, no significant differences were found across groups for usability-related dimensions (effectivity, efficiency, confidence) or later stages of action regulation. Based on findings from study 3, it was not intuitively expected that the perceived support of information acquisition was significantly lower in the explanatory condition compared to the control group. This finding highlights a potential downside of real-time explanatory feedback: if not well-integrated with task demands, it may impair the early phases of information processing and thereby hinder subjective usability. In line with the assumptions of the ART (Frese & Zapf, 1994; Zacher & Frese, 2018), the transparency of signals (i.e., ecodriving feedback) shapes their effectiveness; accordingly, the comparatively low SIPA scores observed in the explanatory group may have negatively impacted subjective action regulation quality (RO3), knowledge acquisition (RO2), and objective driving performance (RO1).

The subjective quality of action regulation did not increase in the condition receiving only recommendations compared to conventional consumption information, which challenges

previous evidence of positive effects of speed recommendations or guidance on performance and perceived usefulness (Allison et al., 2019; Fors et al., 2015). On the other hand, previous studies also failed to find differences in SUS scores between a conventional display and an alternative feedback approach with higher information aggregation and evaluative elements, even descriptively reporting higher scores for conventional interfaces (Young et al., 2009). In contrast, the generally poorer evaluation of the most complex feedback condition (i.e., additional explanatory feedback) aligns with findings that drivers prefer simple presentation formats and rate complex interfaces less favourably (Manser et al., 2010; Neumann & Krems, 2016).

Considering the findings of all studies, different feedback approaches shape the subjective quality of action regulation in differentiated ways. While explanatory formats can support *mental model* development and correction, they may simultaneously challenge drivers' perception of usable, accessible information, especially under high task load.

To generally conclude, if only immediate performance measures were considered, potential trade-offs might be overlooked—on the one hand, identifying factors that hinder information processing, and on the other hand, better interpreting the absence of short-term performance improvements. This supports the importance of user experience assessments in previous studies (Allison et al., 2019; Brouwer et al., 2015; Colley et al., 2022; Fors et al., 2015; Lee et al., 2011; Meschtscherjakov et al., 2009; Neumann & Krems, 2016; Poolkrajang, 2024; Rakauskas et al., 2010; Rolim & Baptista, 2018; Staubach et al., 2014; Young et al., 2009) and argues for the advantage of more differentiated measurement approaches.

## 9.2. Critical Reflection on Limitations and Future Research

This section outlines several limitations of the present research that should be considered when interpreting the findings. Each point addresses a different methodological or theoretical aspect relevant to the design and implications of the studies.

### Sample Characteristics

Most study participants were university students, a sample that also showed average ATI scores above the scale midpoint and limited driving experience due to their age. This relative homogeneity may raise concerns regarding the external validity and generalisability of the findings to broader populations. Nevertheless, the sample is arguably well-suited to represent less experienced drivers—an important target group for energy-efficient driving interventions. For novice drivers, the ecodriving task demands greater cognitive effort and more conscious

regulation, making them particularly receptive to feedback systems designed to support foundational understanding. Future research should investigate more heterogeneous samples to better understand how increasing driving experience influences the effectiveness and adaptability needs of ecodriving feedback, particularly regarding the amount and depth of information presented.

Moreover, previous reviews have highlighted the tendency of ecodriving studies to rely on small sample sizes, limiting statistical power (e.g., Dahlinger & Wortmann, 2016). While the current research aimed to address this issue, recruiting sufficiently large and balanced samples was not always feasible due to complex data collection procedures (Study 3) or the connection to a preliminary study (Study 2). These constraints should be acknowledged when interpreting the scope and robustness of the statistical analyses.

### **Task Simplification and Context Constraints**

The simulated environments used in Studies 2 and 4 lacked realistic traffic dynamics, particularly interactions with other road users. While the core manoeuvres were included and the driving simulation validated (Gödker et al., 2024), the still reduced realism limits ecological validity.

Study 1's tightly controlled setup, including continuous gaze fixation, was geared toward a foundational understanding of consumption display's impact, rather than real-world transfer. Even under these idealised conditions, participants showed biased perception, highlighting the fundamental challenge of awareness formation.

In Study 3, constraints in participant recruitment and the technical complexity of field-based data collection necessitated shorter driving durations. This limited participants' behavioural variability, reduced the opportunity for meaningful practical engagement, and likely curtailed the consolidation of new driving strategies. Future research should aim to extend the duration and frequency of field-based measurements to strengthen the ecological scope and robustness of findings.

Taken together, while the experimental constraints enabled rigorous internal validity and targeted hypothesis testing, they also introduce limitations in terms of generalisability to naturalistic settings. These trade-offs are typical in applied cognitive and human factors research, yet they should be carefully considered when interpreting the real-world applicability of the current results.

### **Use of Self-Reported Data**

Self-reported measures, particularly for perceived knowledge and support, are susceptible to social desirability bias (Nederhof, 1985; Podsakoff & Organ, 2016). Although participants in this study did not directly compare multiple feedback approaches, which might otherwise amplify a bias toward favouring one type of feedback, this concern remains especially salient when assessing competence-related constructs. While social desirability bias is particularly problematic in domains involving socially sensitive or personal issues, and the validity of social desirability scales has been questioned (Lanz et al., 2022), future studies may nonetheless benefit from incorporating established prevention and detection strategies (Larson, 2019; Nederhof, 1985; Podsakoff & Organ, 2016).

In addition to self-report scales, the study employed complementary assessments of verbalisable knowledge to provide a more differentiated picture of participants' actual understanding. Moreover, the measures of perceived support were explicitly designed to capture subjective impressions rather than objective correctness, making them valid within the intended interpretive framework.

### **Subjective Coding**

Coding of tip accuracy in Study 2, while guided by AI-generated coding and demonstrating excellent interrater reliability between AI and researcher coding ( $\kappa = 0.85$ ), still involved researcher input and prompt design, which may introduce potential biases in framing and interpretation. At the same time, several methodological challenges remained, particularly regarding the impossibility of entirely eliminating inconsistencies and errors in AI-based coding, which necessitated manual corrections. Nonetheless, efforts were made to systematise the coding procedure and transparently report the approach. Coding templates were refined based on expert feedback, strengthening analytic consistency.

### **Applying Ideal Reference Standards**

Future research should extend this work by developing a deeper understanding of the extent to which *mental model* enhancement is necessary and beneficial. Such investigations ought to balance *mental model* development with considerations of user experience, workload, and overall performance, instead of aiming to cultivate expert-level knowledge in all drivers.

### **Manipulation of Feedback Conditions**

The feedback conditions in the experiments varied not only in their degrees of automation (see Section 2.4) but also in some studies along multiple dimensions, including modality, amount of information, timing, and metric. This limits the ability to isolate the specific contributions of individual feedback components to distinct aspects of the coupled driver–system control loops.

Future research should aim to systematically manipulate individual feedback dimensions—such as comparing raw consumption values, higher-level analysis (e.g., weighted reasons for consumption), and presenting consumption target values—to better understand how different stages of information processing are supported. The developed subjective scales, such as perceived support of action regulation, can support distinguishing between feedback approaches regarding informational depth and cognitive alignment.

### **Challenges in Capturing Mental Models**

As explained in Section 2.2, assessing *mental models* presents substantial methodological challenges. Expert knowledge, in particular, is often deeply embedded and difficult to articulate verbally (Endsley, 2000). Although the present research employed a multi-method approach—including subjective ratings of perceived knowledge, coding of verbalisable knowledge, and perceived support of the *mental model*—each measure has limitations. However, an alternative approach like correct/false knowledge scales risk oversimplification and susceptibility to response biases, especially when statements are phrased in universally agreeable terms (e.g., “A sporty driving style [...] leads to higher consumption” or “Keep the proper distance from the vehicle in front and avoid unnecessary emergency braking”; Günther et al., 2019; Lai, 2015).

Despite these challenges, it is important to note that examining *mental models* remains central. While some researchers advocate measuring *situation awareness* (e.g., Wickens, 2015), it is grounded in the structure and accessibility of underlying *mental models*. Therefore, a refined understanding of mental representations remains critical within the constraints of available methods. This supports a complementary measurement strategy integrating multiple assessment forms rather than relying on a single indicator.

The inclusion of perceived support of the *mental model* adds additional valuable insight. For instance, Study 4 revealed group differences in perceived support of the *mental model* that were not paralleled by differences in self-reported ecodriving knowledge, suggesting that these constructs capture distinct, non-redundant aspects. This suggests that human factors perspectives can provide valuable complementary insights to traditional measures of short- and

long-term learning outcomes by capturing aspects such as the perceived alignment between feedback and cognitive integration processes, constituting a distinct and meaningful dimension of feedback effectiveness.

Future research should explore how perceived support, subjective knowledge, actual knowledge, and perceived gaps between capability and task demands jointly predict short- and long-term performance. Divergences between perceived and actual competence warrant more refined measurement strategies, such as examining comfort zones regarding task difficulty and adaptive feedback based on driving competence and preferences.

It is also important to consider variation in knowledge measures across studies. Study 1 assessed technical-mathematical knowledge items, whereas Studies 2 and 3 employed previously developed items by the research group focused on ecodriving knowledge. In contrast, Study 4 used a revised item set incorporating adapted items to better reflect the *know-how* regarding various elements of the control loop (input, comparator, output) and the *know-why*. These differences must be considered when interpreting the comparability of knowledge-related results across studies.

### **Goal Conflicts and System Transparency**

In the field study, participants indicated their agreement with various reasons for not being able to drive energy-efficiently, including time pressure, traffic conditions, expectations of other road users, comfort, working load, autonomy, task difficulty, and driving safety. Not reported group comparisons confirmed that the extent of experienced conflicts did not significantly differ across conditions, ensuring comparability in evaluating the effects of the informational approaches. However, such goal conflicts were largely absent in the simulator-based studies, where the experimental instructions prioritised energy efficiency, and scenarios typically excluded traffic or other road users, except one driving sector in Study 4. However, real-world driving inherently involves balancing multiple, often competing, goals—such as energy efficiency, safety, comfort, and punctuality.

Driving behaviour is therefore regulated by person-specific goals and their prioritisation or balancing (e.g., Dogan et al., 2011). Consequently, the success of action regulation depends not only on implementing specific strategies to reach the ecodriving goal but also on how individuals manage the interrelationships between multiple goals (Kung & Scholer, 2020, 2021). Thus, goal balancing may also moderate both the effectiveness and subjective experience of ecodriving feedback approaches. Most research has focused primarily on supporting a single goal, such as energy efficiency, on debiasing the time-saving/-loss bias (e.g., Eriksson et al., 2014; Herberz et al., 2019; Peer & Gamliel, 2013), or on goal prioritisation and

balancing in the context of driving safety (e.g., Schmidt-Daffy, 2012; Schmidt-Daffy et al., 2013). Future research should aim to better understand how drivers balance multiple competing goals depending on personal characteristics and situational demands, and how this influences the generalisability of feedback effects and implications for ecodriving system design.

In Studies 2 and 4, the systems' algorithm made trade-offs between time and energy without making this decision logic transparent to drivers. This lack of transparency may have impaired participants' understanding and trust in the system's suggestions. Qualitative feedback indicated that several participants lacked clarity about how recommendations were generated, which likely affected *mental model* formation and compliance. The system's trade-offs may not reflect drivers' situational or personal goal preferences.

Accordingly, future ecodriving approaches should (1) increase the transparency of system decisions regarding goal trade-offs, (2) examine the effects of different trade-offs on experience and behaviour, and (3) explore the effects of adaptive feedback approaches tailoring trade-offs to individual behaviour.

### **Design Limitations and Power**

Studies 2 to 4 employed between-subject designs. While adequate for the relevant research questions, they may lack statistical power and thus sensitivity to detect subtle differences. Especially regarding comprehension-based feedback approaches, within-subject or mixed designs are challenging to implement as acquired knowledge also influences the following conditions. Besides, this would increase study length and thus also the recruitment complexity. However, enhancing power through design efficiency (e.g., Time [pre, post] x Group [generic vs. elaborated tips]) remains a key challenge for future research.

### **Scale Development**

In the development of the scales perceived support of action regulation and perceived support of the *mental model* within action regulation, several steps were conducted in line with best practice guidelines for scale development (e.g., Boateng et al., 2018; Cronbach & Meehl, 1955). These include the conceptualisation of the constructs, the development of items, and pre-testing procedures. However, additional psychometric validation steps remain to be completed. These include exploratory and confirmatory factor analyses, the assessment of construct validity and reliability, as well as cross-validation and generalisability testing across independent samples.

### 9.3. Contribution to Psychological Research

Several theoretical, methodological, analytical, empirical, and applied contributions of this dissertation advance the field of engineering psychology, particularly in the context of ecodriving support systems for BEV.

#### Theoretical Contributions

The dissertation addresses multiple conceptual and empirical gaps in research on ecodriving feedback for BEVs—vehicles that play a key role in sustainable mobility but remain underrepresented in psychological research. Moreover, prior studies often lack a theory-driven differentiation between types of feedback and their underlying cognitive mechanisms. This dissertation systematically integrates psychological theories and findings of mental representations (e.g., Baumann & Krems, 2009; Carroll & Olson, 1987; Endsley, 2000, 2012; Wickens, 2015) and information processing stages (Wickens & Carswell, 2021) into models of adaptive behavioural control (Carver et al., 2015; Carver & Scheier, 1982, 1998, 2000; Frese & Zapf, 1994; Fuller, 2005, 2011; Powers, 1973; Summala, 2007; Zacher & Frese, 2018). It further extends research on static data visualisations to judgments under dynamic data visualisation, with specific application to driving contexts. The theory-led approach of the dissertation enables a cognitively grounded interpretation of the driver-vehicle interaction, especially regarding mental representations and perceived support for action regulation, two constructs rarely measured systematically in prior work.

#### Methodological Contributions

The dissertation develops a methodological framework that addresses previous shortcomings in user experience research. While earlier ecodriving studies often relied on generic measures of usability, satisfaction, or acceptance (Allison et al., 2019; Colley et al., 2022; Fors et al., 2015; Lee et al., 2011; Meschtscherjakov et al., 2009; Poolkrajang, 2024; Rakauskas et al., 2010; Rolim & Baptista, 2018; Staubach et al., 2014; Young et al., 2009), this dissertation explicitly links usability dimensions to information processing stages (International Organization for Standardization, 2018; Parasuraman et al., 2000; Wickens & Carswell, 2021). Moreover, no prior study has systematically and theory-driven assessed the perceived support of the *mental model* provided by different feedback approaches. Item development was grounded in the definition of *mental models* (Carroll & Olson, 1987). The dissertation's studies contribute a more differentiated and cognitively informed evaluation of drivers' subjective experience. In addition to the primary scale developments (support of action regulation, support of the *mental model* within action regulation), the dissertation also contributes to the stepwise refinement of other

items. Specifically, while Study 3 relied on previously established items from the research group to assess perceived ecodriving knowledge, these items were further developed in Study 4 based on a more fine-grained theoretical anchoring. The refinement incorporated dimensions aligned with information processing stages and added facets such as the verbalisability of knowledge, thereby potentially enhancing the diagnostic value of the measure. Besides scale development and refinement, Study 1 introduces a novel experimental method for capturing energy efficiency judgments in dynamic magnitude perception. Moreover, the dissertation employs a mixed-method approach for analysing action regulation, mental representations and heuristic information processing—including the *Thematic Analysis* (V. Braun & Clarke, 2006) of qualitative data, consideration of open-ended responses, theory-driven item development, objective behavioural data (vehicle logging data, high-fidelity driving simulator, controlled online experiment), and also AI-based quantification. The latter was validated through coding comparison with human ratings to ensure robustness.

### **Conceptual and Analytical Contributions**

The dissertation systematically applies psychological theories to drivers' interaction with BEVs and the design and classification of feedback approaches. Feedback approaches are discussed based on their role in the self-regulatory processes, cognitive mechanisms, as well as the GALA framework (Parasuraman et al., 2000; Ruscio et al., 2024). Furthermore, a systematic literature search identifies theoretical and empirical research gaps, contributing a roadmap for future research on ecodriving feedback.

### **Empirical Contributions**

The dissertation comprises four empirical studies that systematically investigated ecodriving feedback approaches for BEVs. Together, these studies contribute several novel insights:

- Study 1 introduced a novel method to assess energy efficiency judgments under dynamic magnitude perception. It revealed systematic estimation biases in real-time consumption displays shaped by magnitude characteristics (i.e., estimation difference is greater with higher peak height and shorter peak duration). Moreover, interindividual influences (i.e., ATI and prior domain-specific knowledge) are identified, which shape biased judgements and suggest the relevance of user-specific processing strategies.
- Study 2 provides insights into substantial knowledge gaps and limited knowledge accuracy. Interestingly, although subjective uncertainty differed between conditions, driving performance remained comparable, highlighting a potential dissociation between perceived and actual quality of action regulation. Furthermore, verbalisations

of information relevant in the input function differed depending on the feedback approach, suggesting drivers try to make recommendations explainable based on their perception instead of blindly trusting them.

- Studies 3 and 4 examined know-how-and-why feedback and showed that it particularly enhances perceived support of the *mental model* and driving performance compared to less elaborated or alternative approaches (i.e., speed recommendations). While Study 3 demonstrated higher subjective quality of action regulation regarding various information processing stages, Study 4 suggests that several constraints (e.g., feedback modality, working memory capacity, feedback timing, conflicts with other system support) may attenuate these benefits. Additionally, Study 3 replicated and extended prior findings from Sureth et al. (2019) on HEV in a more controlled field setting with BEVs—thereby validating core assumptions regarding feedback effects on *mental model* development.

These studies jointly support the theoretical claims regarding the role of *mental model* support in action regulation and provide a solid empirical basis for the conceptual framework developed in the dissertation.

### Applied and Interdisciplinary Contributions

The developed methods and findings enable a more differentiated and user-centred evaluation of future feedback approaches. Based on empirical results, design recommendations can be derived for explanatory feedback, training interventions, and recommender systems, such as:

1. **Design dynamic visualisations to reduce perceptual biases.** Real-time displays are prone to systematic misjudgements due to salient characteristics (e.g., peak height and duration), distorting users' dynamic magnitude perception. This dissertation highlights this critical perceptual bias, demonstrating that users' decision-making and system interaction may be influenced by biased perceptions rather than actual efficiency. Recognising and addressing these biases is essential for designing human-centred systems that align perception with real performance, enhancing actual effectiveness, not merely subjective experience. Consequently, visual feedback should be evaluated for interpretability and adjusted accordingly, for example, through moving averages, reference values, or highlighting cumulative effects.
2. **Adapt feedback to user traits such as ATI and prior knowledge.** Drivers differ in how they process feedback based on ATI (Franke, Attig, et al., 2019) and domain-specific knowledge. Adaptive feedback may enhance both perceived usefulness and actual effectiveness.

3. **Explicitly support causal understanding.** Feedback systems should foster users' *mental models* by explaining the causal relationships between actions and energy outcomes (e.g., verbal explanations of how and why, including the effects of pedal use on system states, the concept of neutral gliding, or conversion losses), rather than merely issuing prescriptive driving recommendations or raw efficiency-related data. Such explanations support knowledge acquisition and generalisation across contexts, enabling more adaptive regulation.
4. **Increase system transparency of recommendations.** Ecodriving recommender systems should disclose the rationale behind suggestions (e.g., speed adjustments), including which variables are considered and how they are weighted (e.g., air resistance, conversion efficiency, other road users, future road course or traffic light phases, actual speed, speed limits, or time constraints). This is particularly important when recommendations deviate from driver expectations or when SIPA is low. Transparency strengthens trust and promotes effective integration of system advice into user decisions.
5. **Ensure context-sensitive feedback.** The effectiveness of know-how-and-why information as explanatory feedback seems to depend on timing, modality, and drivers' cognitive load. Well-designed systems should deliver verbal explanations in complex environments when users are most receptive—such as low-demand phases (e.g., red traffic light phase, after or before driving)—using channels that minimise interference with primary tasks (e.g., auditory feedback), and selectively based on informational relevance (e.g., following behavioural errors).

Moreover, the developed instruments offer a foundation for assessing critical human-automation issues, such as the "out-of-the-loop" phenomenon or judgement formation based on dynamic data visualisations, and contribute to developing cognitively aligned (driver) support systems. The research provides foundational insights transferable to future, more autonomous ecodriving systems. As automation increases, human roles shift from active information acquisition and analysis towards supervisory control, where the core challenge becomes decision selection: determining when and whether to trust, override, or adjust automated behaviour. In such contexts, accurate and actionable *mental models* allow users to anticipate system behaviour, detect anomalies, and intervene appropriately. However, with reduced hands-on experience in highly automated systems, there is an increased risk of *mental model* mismatches, leading to delayed reactions, misplaced trust, or inefficient interventions. Therefore, systems must actively support users in building and maintaining correct *mental models* through explainable, predictive feedback and system transparency.

## 10. Conclusion

This dissertation contributes to understanding human factors in ecodriving by examining how various feedback approaches affect drivers' perceptions, judgements, knowledge, user experience, and energy efficiency in BEVs. Its contribution lies in integrating and extending psychological theories, addressing gaps identified by a systematic literature review, and soundly exploring various feedback approaches.

Grounded in theories of adaptive control and action regulation, human information processing, and the central role of *mental models* for goal achievement, four empirical studies address theoretical and applied aspects of human-centred design. Users' interactions were examined across simulated driving environments, a field study, and an online experiment. Methods included *Thematic Analysis*, a new experimental paradigm, and initial steps in scale development, contributing to advancing theory and practice in engineering psychology.

Study 1 laid the conceptual foundation by extending research on heuristic processing and bounded rationality to ecodriving and dynamic magnitude perception. It also identified interindividual differences influencing these cognitive challenges.

Study 2 expanded on this by analysing knowledge gaps, performance, and uncertainty using a consumption display (addressing time representation more effectively than heuristic-prone consumption bars) and a recommendation display of optimal speed, compared to a no-support condition. Findings revealed persistent misbeliefs and generally inaccurate verbalised tips and technical reasoning, with no significant differences in energy consumption, but differences in subjective uncertainty. This also underlines the importance of considering performance and user experience to assess feedback effectiveness.

Study 3, building on the prior studies, introduced comprehension-based feedback. Elaborated tips explaining how and why to drive efficiently in specific manoeuvres enhanced drivers' perceived knowledge, *mental model* support, operational behaviour, and perceived support in action regulation.

Study 4 explored such elaborated feedback as explanatory information within a recommendation system. While ecodriving performance and perceived *mental model* support were highest in the explanatory condition, future designs must consider constraints such as impaired information acquisition, cognitive load, and information processing awareness. These factors underscore the need for feedback that is transparent, coherent, and adapted to driving demands and cognitive needs.

The studies demonstrate that ecodriving feedback can foster energy-efficient behaviour and knowledge. Its effectiveness, however, depends on the interplay between fostering adequate *mental models*, support within distinct processing stages, contextualisation, and cognitive prerequisites (e.g., prior knowledge, ATI, cognitive capacity). These findings also highlight the difficulty of substantially improving action regulation through typical support approaches, especially among drivers with limited BEV experience. Feedback must account for systematic biases in information processing and support developing and refining adequate *mental models*. To avoid blind spots in assessment and design, evaluation should go beyond classical performance metrics by including user experience and *mental model* development. The developed scales, perceived support of action regulation and perceived support of the *mental model*, enable differentiated analysis of cognitive processing and directly inform the design and evaluation of broader human–system interaction.

Practically, findings show that drivers benefit most from feedback that supports their understanding of why and how to drive efficiently. Performance, knowledge, and perceived support may suffer without such support. The positive impact of comprehension-based approaches underscores their relevance. Drivers' potential is constrained without adequate mental representations, limiting situation awareness, goal achievement, and confidence. Crucially, the aim is not perfect *mental models* or judgment accuracy, but to optimise the trade-off between performance and user experience, supporting drivers in leveraging the vehicle's technical potential.

In sum, a systematic analysis of perception, judgements, knowledge, behaviour, and user experience establishes a foundation for ecodriving feedback that accommodates the complexities of the driving task.

## **11. Declaration of Generative AI and AI-Assisted Technologies**

During the writing process of this dissertation, I used OpenAI (OpenAI, 2025) and Grammarly (Grammarly, 2025) to improve readability through reformulations and language enhancement. After employing these tools, I thoroughly reviewed and edited all relevant parts, and I take full responsibility for the content.

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